DEVELOP A FERTILIZER PRICE FORECASTING MODEL TO ASSIST WITH FARM MANAGEMENT DECISIONS

A Thesis

by

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ABSTRACT

Fertilizer is critical to modern production agriculture. The primary components of fertilizer, nitrogen (N), phosphorus (P) and potassium (K) provide crops the nutrients required to achieve optimal production. Across all types of U.S. crop farms, fertilizers account for roughly 20 percent of crop production expenses. Over time, fertilizer prices have been quite variable. Farmers typically order or book fertilizer needs in the late fall well in advance of planting or wait until closer to planting. The decision to book fertilizer in advance verses buying when needed is a business management issue for many farmers. This study uses a vector autoregression model to forecast fertilizer wholesale fertilizer prices. A decision analysis for two purchasing strategies that test seasonal changes of fertilizer prices is explored. Finally, a price wedge is added to two regional forecasts to reflect retail fertilizer prices. The price forecasts show that fertilizer prices have decreased in the last six months and will continue to remain steady in the near future. Results of the decision analysis did not indicate that there were seasonal changes between months.

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CHAPTER I

INTRODUCTION

Fertilizer is critical to modern production agriculture. The primary nutrient components of fertilizer, nitrogen (N), phosphorus (P) and potassium (K) provide crops the primary macronutrients required to achieve optimal production. Across all types of U.S. crop farms, fertilizers account for roughly 20 percent of crop production expenses. Over time, fertilizer prices have been quite variable (Figure 1). Farmers typically order or book fertilizer needs in the late fall well in advance of planting or wait until closer to planting. Purchasing prior to the end of the tax year is often used to manage taxes as well as take advantage of lower prices that sometimes occur before the end of the year. The decision to book fertilizer in advance verses buying when needed is a business management issue for many farmers. Historically, supply and demand factors have influenced price volatility in fertilizer markets which have impacted farmer purchases of fertilizer as well. Additional information about future fertilizer prices will enable producers to make more informed decisions regarding their fertilizer purchases.

Objectives

The primary objective of this research is to develop forecasting models of U.S. average retail prices for nitrogen, phosphorus, and potassium fertilizers. A secondary objective is to develop region specific retail price forecasts for Texas and the Corn Belt that will enable producers to evaluate the relative cost of the primary types of fertilizer used in the state. Furthermore, a comparative cost analysis between purchasing fertilizer in advance and buying it at the time of need will be explored. Lenders, landlords, and those associated with farming operations will benefit from knowing price trends in the fertilizer industry. The following chapters will outline the relevant literature, the data and methodology, and the results of the analysis.

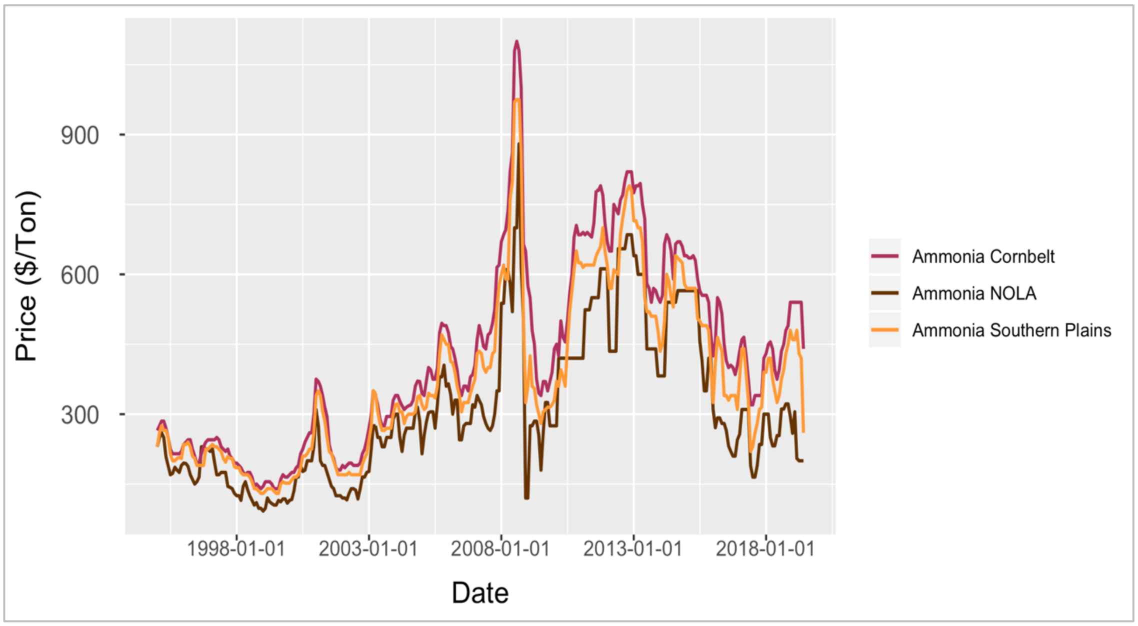

Figure 1. 1. Monthly Ammonia Price (1995-2019)

CHAPTER II

LITERATURE REVIEW

Literature Introduction

There is a sizeable quantity of literature on fertilizer products, specifically, fertilizer demand. Despite the abundance of foundational research, only a few agricultural economists have developed models to forecast fertilizer prices. Much of the literature involving forecasts of fertilizer prices is either outdated, concentrated to a specific region, or focused on a certain fertilizer type. This literature review begins with the history of the fertilizer industry, followed by the definitions of the fertilizer products used in production agriculture, fertilizer demand studies, and fertilizer price forecasts.

The History of Fertilizer

The use of fertilizer in production agriculture began as early as the Neolithic age. Fertilizers became more prominent as agriculture evolved and the world population grew. The birthplace of modern agriculture began in the Fertile Crescent of Mesopotamia when humans made the transition from hunting and foraging for food, to producing annual row crops such as wheat and barley. Land was not a limitation during that time, as the world population was only around 8 million people. Many people engaged in subsistence farming to feed their families. Organic fertilizers, such as manure, bone, and ash were sometimes used to increase yields. These small operations would continue until the world population increased and arable land was used for towns and cities (Evans 1980).

The foundation of the modern fertilizer industry began in 1840. The population had reached over one billion, and the need to produce food more efficiently became paramount. Chemists such as Justus Liebig and John Lawes conducted experiments with chemicals such as ammonia and sulfuric acid. Soon thereafter, the markets for the chemicals we use today (nitrogen, phosphorus, and potassium) would develop. Over time, production of these elements have become more sophisticated (Russell and Williams 1977; Achorn and Balay 1985).

From 1950-1970, a worldwide influx of farming technology sparked the Green Revolution. The initiative would emphasize high crop yields on fewer acres by using hybrid plant varieties, new irrigation practices, and increases in fertilizer use. The modern approach to chemical fertilizers began during the Green Revolution (Borlaug 1973).

Types of Fertilizer

Nitrogen, phosphorus, and potassium are the three basic macronutrients necessary for crops to flourish. When used according to prescribed rates, each can provide plants with the optimal amounts of nitrogen, phosphorus, and potassium for growth and metabolic processes.

Nitrogen

Nitrogen (N) assists crops in growth and development by the production of proteins such as amino acids and the enzyme chlorophyll. There is approximately 35,000 tons of nitrogen in one acre of land, so the need to maintain N levels for farming operations is critical (Kansas State Agronomy). The United States is one of the largest producers and consumers of nitrogen products worldwide (U.S. Geological Survey, 2019).

Anhydrous ammonia is composed of 82 percent nitrogen and 18 percent hydrogen and is in a gaseous state in its basic form. To be useful to agricultural producers, the compound must be pressurized into a liquid form. Proper care and storage techniques must be considered to avoid accidents, as it is known to cause explosions if mishandled. Anhydrous ammonia can cause damage to seeds or root structure unless diluted in water, therefore it must be injected into the soil so as to not damage the seeds. Furthermore, the product must be applied at proper distances away from the plant and at appropriate moisture levels so that it can change into a more absorbable nutrient for the crop. Many farmers apply anhydrous ammonia prior to planting to avoid any damage to the seeds (Kansas State Agronomy). Around 50 percent of the domestic ammonia supply is located in Louisiana, Oklahoma, and Texas because of their large reserves of natural gas, the primary input for ammonia. Anhydrous ammonia is the foundational component for nitrogen fertilizer products and is used to produce other N products such as urea, ammonium nitrate, ammonium phosphate, and ammonium sulfate (U.S. Geological Survey, 2019).

Ammonium nitrate is produced from ammonia and nitric acid. It is produced into a granulated form. Ammonium nitrate is known to provide nutrients to the plant for several weeks. This component can tend to be more expensive than other fertilizers, making it less popular among producers.

Urea is produced by combining ammonia with carbon dioxide. Carbon dioxide is a by-product of ammonia production, making the production of urea relatively economical. Urea has become one of the most popular granular fertilizers on the market because of its affordability and practical storage properties. While more manageable, urea can suffer from the higher levels of volatilization, or vaporization. Improper application, high pH soils, crop residues from no-till farming practices, and areas with sandy soils have a higher risk of losses to volatilization. Proper management practices can eliminate the risk of loss.

Urea Ammonium Nitrate (UAN) is a liquid mixture of water, urea, and ammonium nitrate. UAN is widely used among producers because of its versatility with many production practices. UAN can be mixed with insecticides, fungicides, and other agricultural chemicals, as well as applied directly to the plant (if managed with proper dilution methods). It is also suitable for application with irrigation water if needed. UAN is generally more expensive than products like anhydrous ammonia and has the potential for volatilization if mismanaged. It is usually graded at 28 percent or 32 percent of nitrogen (Kansas State Agronomy).

Phosphorus

Phosphorus (P) is a critical macronutrient for plants, playing a large role in metabolic processes such as photosynthesis. Most plants and soils are naturally more deficient in phosphorus than other macronutrients. P fertilizers can increase yield, encourage growth during unfavorable climates, increase root structure, and improve disease tolerance. Rock phosphate is mined out of the ground. Historically, the United

States has imported phosphates from Morocco and recently, Peru. Two phosphate products, monoammonium phosphate (MAP) and diammonium phosphate (DAP) are combined with ammonia and are products of interest for the current study due to their popularity with farmers.

Monoammonium phosphate, or MAP, is a one to one ratio of ammonia and phosphoric acid. It is produced in a granular form and is easily storable. MAP is an acidic fertilizer and works best in soils with neutral or high pH levels. It does not cause harm to germinating seeds. Farmers can apply MAP in a variety of ways, including uniformly spreading and tilling the product near the plant root structure. Diammonium phosphate, or DAP, provides the same amount of phosphorus to plants as MAP. The extra ammonia molecule present adds more N to the soil, however, DAP must be managed more intensively. It is the most widely used phosphorus fertilizer available (Kansas State Agronomy).

Potassium

Potassium (K), or potash fertilizer is a unique compound, as it activates several enzymes within plants to complete metabolic processes. Potassium allows the plants to retain water and transfer carbohydrates into energy which increases plant growth and yields. It also aids in the production of proteins within plants. Potash fertilizer must be placed in the root zone via banding, an application method that places fertilizer two inches below the seed of the crop. K fertilizers are mined underground and are usually sold in granular form. The United States has historically imported potash from Canada (Kansas State Agronomy).

Fertilizer Application

Fertilizer can be applied to the soil in granular and liquid forms (Achorn and Balay 1985). Some producers have found livestock manure to be a viable source of fertilizer for its economic benefits (Lory et al. 2008; Jokela 1991).

Optimal application rates for fertilizer are dependent on the type of soil and crop. Desired economic fertilizer rates were studied to determine the most profitable levels of N, P, and K (Godden and Helyar 1980; Forster 1985; Cerrato and Blackmer 1990). Baethgen et al. (1989) and Scharf et al. (2005) studied the yield maximizing fertilizer rate for grains using linear programming models.

Some crops, notably soybeans and peanuts, are classified as legumes and add nitrogen to the soil. Legumes require a smaller rate of N, P, and K than other crops. Salvagiotti et al. (2008) studied the amount of nitrogen that is fixated in the soil from soybeans and the economic and yield impact on grains the following year.

Recent advancements allow producers to apply fertilizer at variable rates across a field. This technology is administered by mapping technology of the field (Wollenhaupt 1994) and computerized application equipment. Fertilizer is utilized more efficiently by applying more (or less) chemical in places of need or where there are differing soil types. Studies show that yields and profits increase and costs decrease using this management practice (Babcock 1998; Sawyer 1994; Raun 2002).

Evolution of Fertilizer Types

Technological changes of the industry have come in the form of controlled and slow release fertilizers. Granules of nitrogen, phosphorus, and potassium (hereby known as N, P, and K), are coated in different polymers to slow the release of chemicals to the plant (Boli 2009). This can improve nutrient absorption by the plant and reduce fertilizer runoff that could potentially damage the environment (Shaviv 1993; Trenkel 1997). These polymers can be multi-layered and improve water retention (Wu 2008).

Factors that affect Fertilizer Price

Most crops require some combination of nitrogen, phosphorus, and potassium. Each of these compounds are correlated with different variables that effect fertilizer price. Huang (2007) denotes a variety of supply and demand factors that may contribute to changes in fertilizer prices. Some of these factors include: rising input costs, transportation and handling, and economic and population growth. Mergers within the industry have led to higher prices (despite lower costs of production inputs) due to a monopolized market structure (Humber 2014). Producers have adopted inventory management techniques that have helped reduce price volatility.

Natural gas is the primary input for nitrogen fertilizer with 74 percent of the energy required to make N fertilizer coming from the substance (Twaddle 1982). Historically, volatile natural gas and oil prices have led to higher fertilizer prices (Pindyck 2003; Huang 2007), however, recent advancements in drilling technology, such as fracking, have led to a more abundant supply of natural gas (Joskow 2013). Phosphate rock, the primary input for P fertilizer, is concentrated in certain parts of the world. Most of the phosphate mines are located in either China, Morocco, or the United States (Geman et al. 2013). China has been reluctant to trade their reserves and imposed a 135 percent tariff on exports. The United States has only 25 years left in reserves and imports a large portion of phosphate rock from Morocco (Cordell 2009). The price of P fertilizer is expected to increase over time with a limited supply and growing demand. Potassium, also known as potash, is also mined and concentrated in Russia and Canada. There is potential for geopolitical concerns as domestic reserves of fertilizer, particularly P, diminish (Cordell 2009).

Transportation and handling of fertilizer incurs significant costs for producers and consumers of fertilizer. Fertilizer is a bulky commodity and, depending on the product, can yield costs by ship, barge, rail, and truck. Distribution bottlenecks pose challenges to retailers and farmers that require fertilizers at certain times of the year. Oil and gas prices are notable price shifters because most fertilizers are imported from foreign countries or hauled domestically from concentrated supply locations. Special care must be taken during transport, as some fertilizers (such as anhydrous ammonia) are subject to explosion. Some chemicals require refrigerated or pressurized containers to transport (Huang 2007).

Handling of fertilizer can also impact prices. Retailers must make significant investments to comply with government regulations for storage and handling procedures of liquid and granular fertilizer. Liquid fertilizers are subject to spillage, thus requiring dikes, rinse tanks, and sophisticated plumbing that can contain large spills. Dry fertilizers require mixers and equipment to transport fertilizers to the stalls in the storage area. (Rogers and Akridge 1997).

A growing world population increases demand for food and puts pressure on farmland availability. Producers are tasked with increasing yields on smaller acreage, requiring the use of fertilizer to improve production. According to the World Bank, the population grew 1.2 percent in 2017 (World Bank 2017). Economic growth in developing countries such as China and India has led to increases in consumptions of meat, dairy products, and vegetable oils. This, in turn, leads to higher demand for feed grains and oilseeds. Fertilizer will see growing demand which could lead to higher world prices (Huang 2007).

Inventory management can be a significant factor in farmer purchases of fertilizer. Fertilizer costs are a large expense for agricultural operations, accounting for about 15 percent of production costs (Plastina 2016). Many producers acquire fertilizer prior to planting season to take advantage of lower prices (Kim and Brorsen 2017). Some have tried using the fertilizer futures market to spread out the price risk, however, the market has not worked due to high basis risk (Bollman, Garcia, and Thompson 2003). Moreover, forward contracts and swaps markets are expensive (Kenkel and Kim 2009; Kim and Brorsen 2017). Alternatively, natural gas and corn futures have been more accurate measures determining fertilizer prices (Galbraith 2010).

Demand Estimates of Fertilizer

Fertilizer demand has increased substantially since the Green Revolution. Many agricultural economists have estimated demand estimates for fertilizer. Griliches (1958) found that most fertilizer demand response is dependent on fertilizer price. Griliches' model consists of two parts: a long run demand function and an adjustment equation to account for the time for the fertilizer market to return to equilibrium. USDA data was used to predict the demand functions for N, P, and K. Fertilizer price was included as an explanatory variable. Other input prices, such as wages or land values were found to be insignificant and were not included in the model. Results indicate that as fertilizer prices increase, demand for fertilizer decreases. The R^2 was found to be between 0.96 and 0.98 for each of the estimated models.

Heady and Yeh (1959) estimated regional demand functions for the three primary micronutrients in ten production regions of the U.S. The fertilizer price index, crop price index, lagged cash receipts from farming, production acreage, two time trends, and an income fraction were used in the model. The R^2 is upward of 0.90 for all regions. The study noted that the Southern United States was the most elastic region (although it was inelastic at 0.53) due to the lack of capital for farmers of the 1950's.

Carman (1979) estimated the input demand function of 11 Western states by forming the profit function in terms of output price, the production function, and costs associated with inputs. Using USDA consumption data, Carman takes the partial derivatives of the profit function (with respect to inputs) to estimate demand. Each of the estimates had a negative sign, indicating that increases in fertilizer price lead to decreases in the demand for fertilizer.

Ibach and Adams (1964) predicted aggregate demand by region, but also analyzed specific fertilizer demand by major crops, including corn, cotton, wheat, hay, and oats. Gunjal, Heady, and Roberts (1980) conducted a similar experiment using different crops. A profit maximizing model is used to predict first-order conditions to obtain input demand, the prices of substitute and complementary inputs, and the output price. In each of these studies, different crops have varying elasticities, suggesting that different crops have different demand functions of fertilizer.

Rausser and Moriak (1970) used cross sectional data to study demand. Griliches' model and methodology are used. The results of the research suggest that fertilizer demand has become less responsive to other input costs such as land and crop price while becoming more responsive to its own price as time as elapsed. This indicates that fertilizer has become a significant aspect of commercial farming operations.

Roberts (1986) observed aggregate demand for N, P, and K in the state of Tennessee and attempted to conduct detailed analysis of the cross-price elasticity between the three main fertilizers. Multicollinearity issues determined the cross-price elasticity estimate biased. Own-price elasticities were estimated and displayed results similar to those of previous studies.

Gyawu et al. (1985) predicted a model that included supply, demand, imports, exports, and price estimates of wholesale N, P, and K fertilizer. The wholesale forecasts are used to predict retail prices, along with a wholesale price index and a stock to production ratio. Supply estimates are functions of their own input prices, labor, and electricity while fertilizer demand estimates were estimated based off of their own input prices, corn price, and acreage planted of 20 principal crops. Import and export forecasts included the same variables as the demand and supply estimates, as well as import and export demand. Results of the study indicated that increases in planted acres of principal crops would increase fertilizer demand, which in turn increases imports. The elasticities of fertilizer with respect to corn price were smaller than expected, indicating that a 1 percent increase in price would increase fertilizer demand by 0.334 percent. The evidence in this study suggests that increases in acreage from the Green Revolution led to significant changes to the fertilizer industry.

Fertilizer organizations such as the International Fertilizer Industry Association and the Fertilizer Institute publish outlooks that include similar forecasts of supply, demand, prices, and trade variables (Heffer 2016; The Fertilizer Institute 2018).

Notable Studies

Harry Vroomen (1991) combined regression and time series analysis to predict a short-run retail price forecast of different nitrogen fertilizer products. Monthly time series data from Green Markets was used to generate wholesale price estimates using an autoregressive integrated moving average (ARIMA) model. These prices were then incorporated into a regression model with other explanatory variables to predict retail prices of 14 major fertilizer mixtures. The forecasts were combined to form a producer price index. This methodology accounts for the seasonal trend of fertilizer in the time series model, as well as the explanatory variable of the rail freight index in the regression model. Overall, Vroomen's study provided an accurate forecast of retail fertilizer prices being within 5 percent of the actual price on all but 3 of the estimates. All predicted variables had positive correlations with the exogenous variables, indicating that lagged fertilizer prices and transportation costs have a positive effect on N fertilizer price. The coefficient of determination or R^2 was above 0.75 for all models. Exogenous variables, such as natural gas and crop price, were not included in this model. The other major nutrients, phosphorous and potassium, were not included in his study.

Schnitkey (2016) estimated annual anhydrous ammonia prices using a structural model. The study predicted prices with natural gas and corn price as explanatory variables that were obtained from the Energy Information Service (EIA) and National Agriculture Statistics Survey (NASS). Anhydrous ammonia price data was acquired from USDA Economic Research Service (ERS). The model was estimated using ordinary least squares (OLS) regression. Each of the explanatory variables had positive effects on the price of fertilizer, indicating that as natural gas and corn prices increase, fertilizer prices will also increase. The equation had an adjusted R^2 of 0.88. The results were limited due to the projection of only ammonia. The study emphasizes the rise of natural gas prices until 2006, when a new technology called fracking was introduced in the oil and gas industry. Since then, there have been increases in the supply of natural gas. Anhydrous ammonia prices were highly correlated with natural gas prices until this change. Despite low input prices of natural gas, N fertilizer prices remain constant. Schnitkey suggests that farmers could plant more acres into soybeans to put more pressure on the producers of anhydrous ammonia.

A similar study was conducted by Ibendahl (2017). Anhydrous ammonia prices obtained from the Progressive Farmer annual reports were estimated using OLS regression analysis. This study also uses the USDA reported corn price as a primary explanatory variable. Oil prices, a substitute for gas, was used since there currently is a low correlation between ammonia and natural gas prices (0.01). Using oil price as a substitute yields a higher correlation with N fertilizer price at 0.55. According to the model, corn price is positively correlated with fertilizer price at 0.84. This suggests that as corn price increases, higher nitrogen rates per acre will be applied to the fields to increase corn yields. The study predicts that farmers can expect increases in fertilizer price due to an increasing oil price. Ibendahl explains that since anhydrous ammonia is the basis for most other N fertilizers, it gives the reader an idea of where other fertilizer prices are trending. The assumption that other fertilizer prices are strongly correlated with anhydrous ammonia that it can be used as a viable forecast for P and K is a shortcoming of this study.

Kim and Brorsen (2017) predicted wholesale urea prices out of New Orleans (one of the largest ports for urea in the United States), and compared them with the price forecasts by commercial fertilizer organizations such as Fertilizer Week. A time series model that accounts for heteroskedasticity, also called Generalized Autoregressive Conditional Heteroskedasticity model (GARCH), is used to predict monthly urea prices. Rolling window regression is also used to account for structural changes. A variety of statistical tests are used to determine the accuracy of the prediction. Corn, natural gas, and intermediate fuel oil are used as explanatory variables in the model. Fertilizer Week's free-on-board urea prices from the port of New Orleans are used for estimation. Fertilizer Week's prediction model is then compared with Kim and Brorsen's forecasts. Statistical tests indicate that the forecasts are unbiased. The MAE, a mean-type accuracy measurement tool, was lower in models with explanatory variables, denoting the improved accuracy of the forecast. Kim and Brorsen's forecasts are comparable with Fertilizer Week's and while slightly different, provide unique information about fertilizer prices. This model only forecasts urea prices. Wholesale forecasts are not as useful for farmers because they are limited by the excluded transportation costs that occur at the retail level.

While this model incorporates marine transportation costs, it does not account for rail or trucking that occur as fertilizer is shipped from the ports to the rest of the United States.

From these results, the methodology from the previous literature will provide the current study with the framework to predict monthly retail N, P, and K prices. The most successful forecasting models from previous studies used time series models (Vroomen 1991, Kim and Brorsen 2017). The proposed project will use vector autoregression because of the many variables that are believed to affect fertilizer prices, providing a more accurate estimation of forecasts. Natural gas, crude oil, corn, and exchange rates are included in the model (Schnitkey 2016). The use of exchange rates as a forecasting variable is not found in previous studies. The current model will include exchange rates to account for international transactions, as much of the domestic fertilizer supply is imported. Monthly data will be used to provide a better understanding of when farmers should purchase fertilizer products throughout the year (Ibendahl 2017). There has not been a study that has predicted fertilizer prices at a retail and regional level. Most studies predict fertilizer prices based off of the wholesale port price for ammonia (the basic component of most nitrogen products). The proposed research will use a localized price wedge for many retail fertilizer products at different production regions across Texas. This approach will provide producers with a practical tool for optimal decision making.

CHAPTER III

METHODOLOGY

This research will use vector autoregression to estimate monthly N, P and K prices for the U.S. and regional data will be used to develop estimates for Texas.

Data

Monthly spot price data from January 1995 to July 2019 was obtained from Green Markets, a Bloomberg database. The available data includes the following fertilizer products:

- anhydrous ammonia,
- ammonium nitrate,
- ammonium sulfate,
- diammonium phosphate (DAP),
- monoammonium phosphate (MAP),
- potassium chlorate (Potash),
- urea ammonium nitrate (UAN),
- and urea.

Wholesale prices are available for two production regions: Corn Belt and Southern Plains. Before defining the model used to project fertilizer prices, it is important to establish some foundational information as to the fertilizer products and variables that are included in the model.

The Corn Belt region includes Ohio, Indiana, Illinois, Iowa, Missouri, and Nebraska. These states have historically accounted for a large portion of the corn and soybean crop in the United States. The Corn Belt region will be an effective test area due to the amount of fertilizer purchased, the transportation costs required to get the fertilizer to the region, and the influence the region has on fertilizer component markets.

The Southern Plains region includes Texas, Oklahoma, Kansas, New Mexico, and Colorado. This study area will provide unique perspective on fertilizer prices for Southern crops such as cotton and grain sorghum, and will also give a more realistic expectation of fertilizer price trends for producers in Texas. Allowing multiple price locations for different products will account for transportation costs that are accrued from ports, rail, truck, and barge costs associated with moving fertilizer to different production regions.

Variables identified in the literature review that are thought to influence fertilizer price are included. The U.S. Energy Information Administration (EIA) records natural gas and crude oil data from the Thomas Reuters database. Henry Hub Natural Gas spot price is included in the model. Corn prices are from the National Agricultural Statistics Service (NASS). The West Texas Intermediate crude oil spot price and Thomas Reuters exchange rates from Canada, Russia, and Morocco are included to account for price impacts due to transactions of international trade and logistical expenses. Green Markets fertilizer price data from the ports of New Orleans, Tampa Bay, and Saskatchewan are included to account for production costs, as much of the fertilizer is produced into applicable products around the ports.

Natural gas is a critical input for all nitrogen fertilizers. Approximately 33 Million British Thermal Units (BTU) are required to produce one ton of ammonia (Huang 2007). Over time, the price of natural gas increased until 2008, and has gradually decreased since its peak (Figure 3.1). One hypothesis is that structure of the nitrogen fertilizer industry is limited to a few, large companies. These companies set the price for their product, implying that natural gas will only have an impact on price when it is high. New technology such as fracking has also led to an abundant supply of natural gas. Nevertheless, it remains an important variable to include in the model but may not be as statistically significant as it has been in the past.

Crude oil was included in the model for a variety of reasons. Previous literature suggests that the price of oil and natural gas can be interchangeable because natural gas is usually found in the same location as oil (Ibendahl, 2017). With the decrease in natural gas price in recent years, including crude oil will account for the impact of natural gas on fertilizer prices. Other literature suggests that the price of oil must be included to account for rail, shipping, and trucking costs. Fertilizers incur extensive transportation costs as some products are only available in certain parts of the world. The United States imports fertilizers from many countries worldwide. Fertilizer is shipped from these countries to various ports across the U.S. The commodity is then transported by rail, barge, or truck to various production regions of the country. Each of these types of transportation require some type of oil product for transport. The price of crude oil is reflected in Figure 3.1.

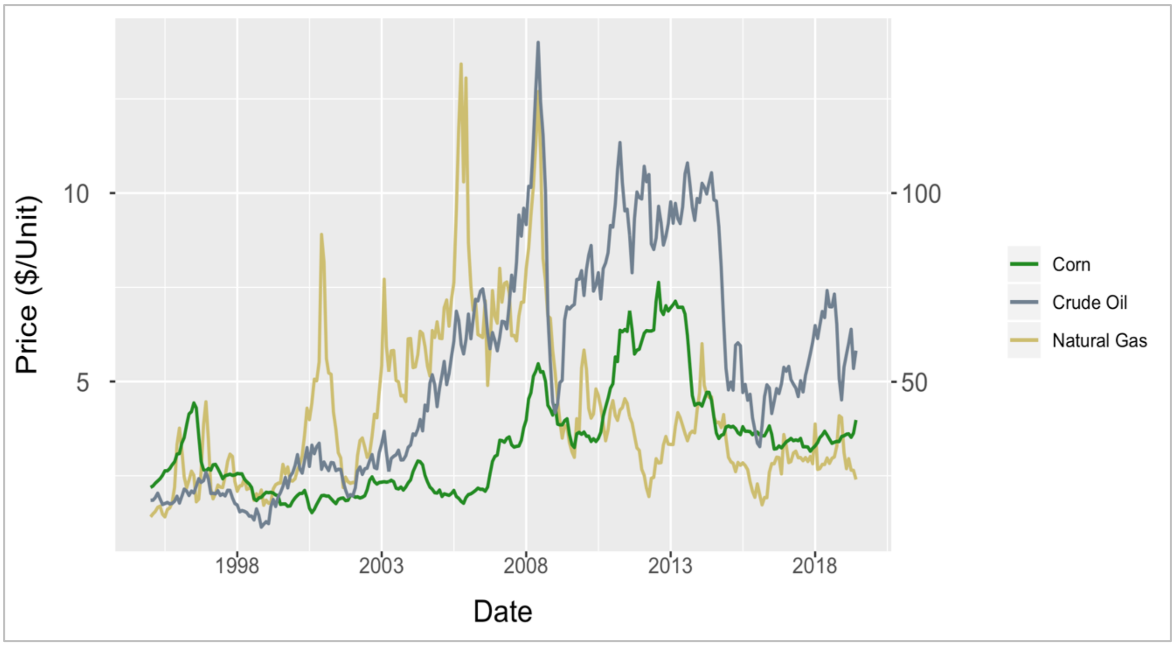

Figure 3. 1 Corn ($ per Bushel), Crude Oil ($ per Barrel), and Natural Gas ($ per BTU) Prices (1995-2019)

The price of corn is included in the model since it requires an extensive amount of N, P, and K relative to other crops (Figure 3.1). Furthermore, corn is grown in every production region in the United States, making it a versatile crop to reflect fertilizer prices in different production regions. The corn price is expected to have a significant positive impact on the price of fertilizer, particularly nitrogen products.

The fertilizer produced in the world is concentrated into a few large corporations that have facilities across the globe. As mentioned previously, the United States imports fertilizer products from several countries around the world, mostly supplied by these few companies. Canada and Russia have abundant resources of nitrogen and potassium resources. Morocco has the largest phosphate reserve in the world at 50 Billion tons (U.S. Geological Survey 2019). Therefore, exchange rates from Canada, Morocco, and Russia are included in the model to account for transaction costs between the exporting country and the United States (Figure 3.2). There were no exchange rates in models from previous literature.

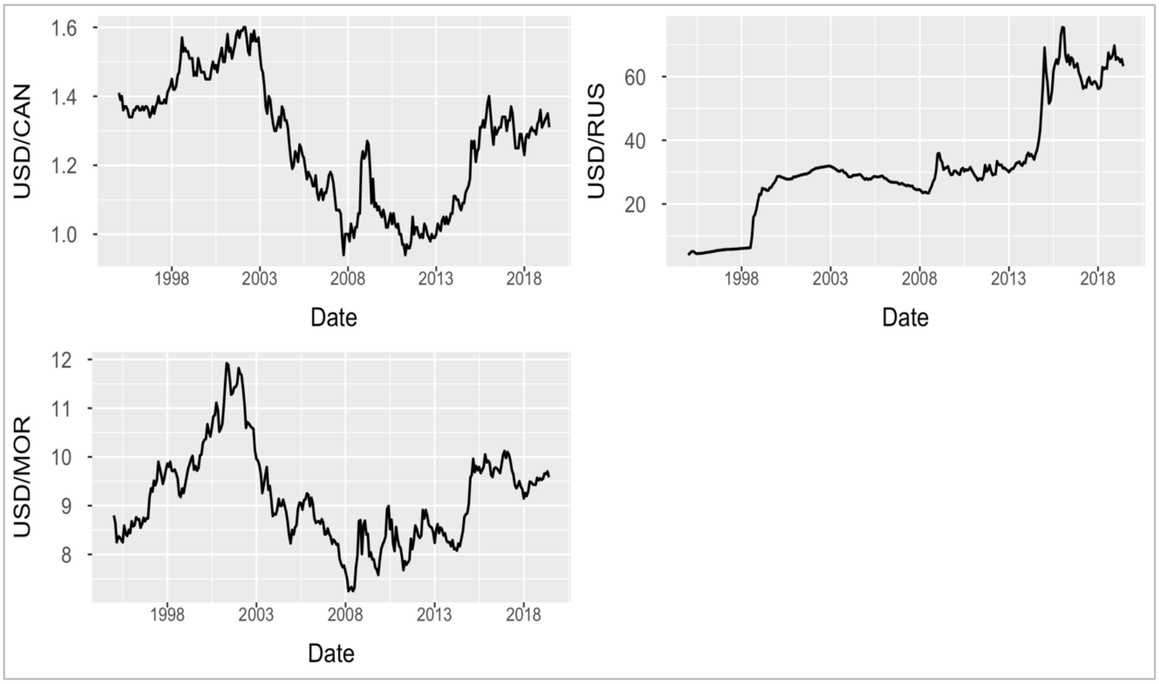

Figure 3. 2 Canada, Russia, and Morocco to USD Exchange Rates

The port of New Orleans is the largest domestic port for all types of fertilizer, accounting for 27 percent of imports and exports (The Fertilizer Institute 2018). New Orleans is a prime location for fertilizer because of its proximity to the Mississippi River, allowing fertilizer to be shipped to the Midwest via barge.

Central Florida is considered to be a large hub for phosphate products. The port of Tampa Bay is the closest accessible port for many phosphate producing countries. Additionally, one of the few domestic phosphorus mines are located in Central Florida, making it convenient location for inland rail transportation. The DAP price utilized in this research represents prices at the port of Central Florida.

The port of Saskatchewan is the largest Canadian port for potash fertilizer production. Much of the K fertilizer imported by the United States comes from this location. Using port data from this location will allow for a wholesale price forecast without any retail or upcountry freight cost.

One limiting factor of the data is the availability of retail fertilizer prices. To compensate for this limitation, the Texas A&M Agricultural and Food Policy Center (AFPC) Representative Farm data is utilized to create a localized price wedge for fertilizer products. The data for the representative farms is developed by interviewing actual crop and livestock producers from various production regions and gathering their expenditures. Retail prices for nitrogen, phosphorus, and potassium are collected from farmers on the AFPC panels and used to calculate a price wedge to reflect retail fertilizer prices in Texas. Production regions analyzed include the Texas Panhandle, South Texas, and the Texas Gulf Coast.

Statistical Estimation Software and Estimation Techniques

The quantitative analysis for this thesis is calculated using R. R is a free programming language and software used for statistical analysis and graphics. R was chosen because of its customizable functions and flexible interface.

Descriptive statistics for each variable are found in Tables 1 and 2. The wholesale fertilizer products are in dollars per ton. The supply and demand variables found in Table 2 are in their respective units. Units for exchange rates are in the respective country's currency per U.S. dollar.

Table 3. 1: Descriptive Statistics for Wholesale Fertilizer Products

Statistic	Mean	St. Dev.	Min	Max
AA Corn Belt	422	203	140	1,100
AA Southern Plains	374	178	130	975
AA NOLA	306	159	92	880
AN Corn Belt	258	105	110	600
AN Southern Plains	245	102	105	570
AS Corn Belt	220	90	112	505
AS Southern Plains	207	84	95	450
UAN Corn Belt	224	101	88	550
UAN Southern Plains	210	95	83	520
Urea Corn Belt	296	135	105	880
Urea Southern Plains	283	131	102	860
Urea NOLA	254	126	85	825
DAP Corn Belt	358	184	160	1,143
DAP Southern Plains	347	178	152	1,100
MAP Central Florida	328	184	133	1,105
DAP Central Florida	318	180	127	1,080
Potash Corn Belt	285	188	101	930
Potash Saskatchewan	249	178	75	780

*Fertilizer products are in Dollars per Ton

*294 Observations of each variable

Table 3. 2: Descriptive Statistics for Supply/Demand Variables

Statistic	Mean	St. Dev.	Min	Max
Crude Oil	53.43	29.50	11.37	139.96
Corn	3.35	1.40	1.52	7.63
Natural Gas	4.15	2.18	1.41	13.42
Canada Exchange Rate	1.27	0.18	0.94	1.60
Morocco Exchange Rate	9.15	0.96	7.25	11.92
Russia Exchange Rate	31.89	17.33	4.01	75.46

*Crude Oil (USD/Barrel), Corn (USD/Bushel), Natural Gas (USD/BTU)

Anhydrous ammonia price at the port of New Orleans, Corn Belt, and the Southern Plains are plotted in Figure 3.3. The New Orleans price registers as the lowest among the three, confirming that the price is lowest at the port. The Corn Belt price is the highest due to transportation costs associated with movement to the Midwest. Ammonia prices increase steadily until reaching a peak in 2008. The implementation of the Renewable Fuel Standard is one plausible explanation, as the demand for corn increased significantly. In response, farmers planted many acres in corn. The cause of the sudden decrease is unknown, however, it corresponds to the housing market crash and the increased supply of corn and natural gas due to the demand of ethanol and fracking technology respectively. Prices recover in 2012, potentially due to favorable rains and increased commodity prices. Since 2012, prices decreased gradually but have followed an increasing trend since the end of 2017. Since ammonia is the basis for many other fertilizer products, other plots show similar price trends (Figure 3.4).

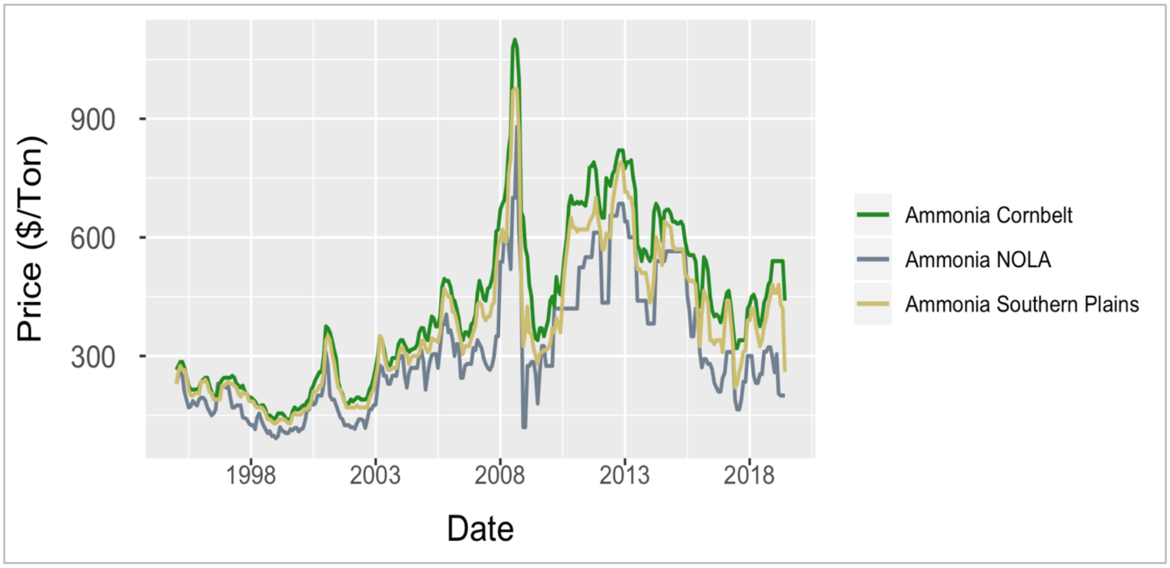

Figure 3. 3 Monthly Anhydrous Ammonia Price (1995-2019)

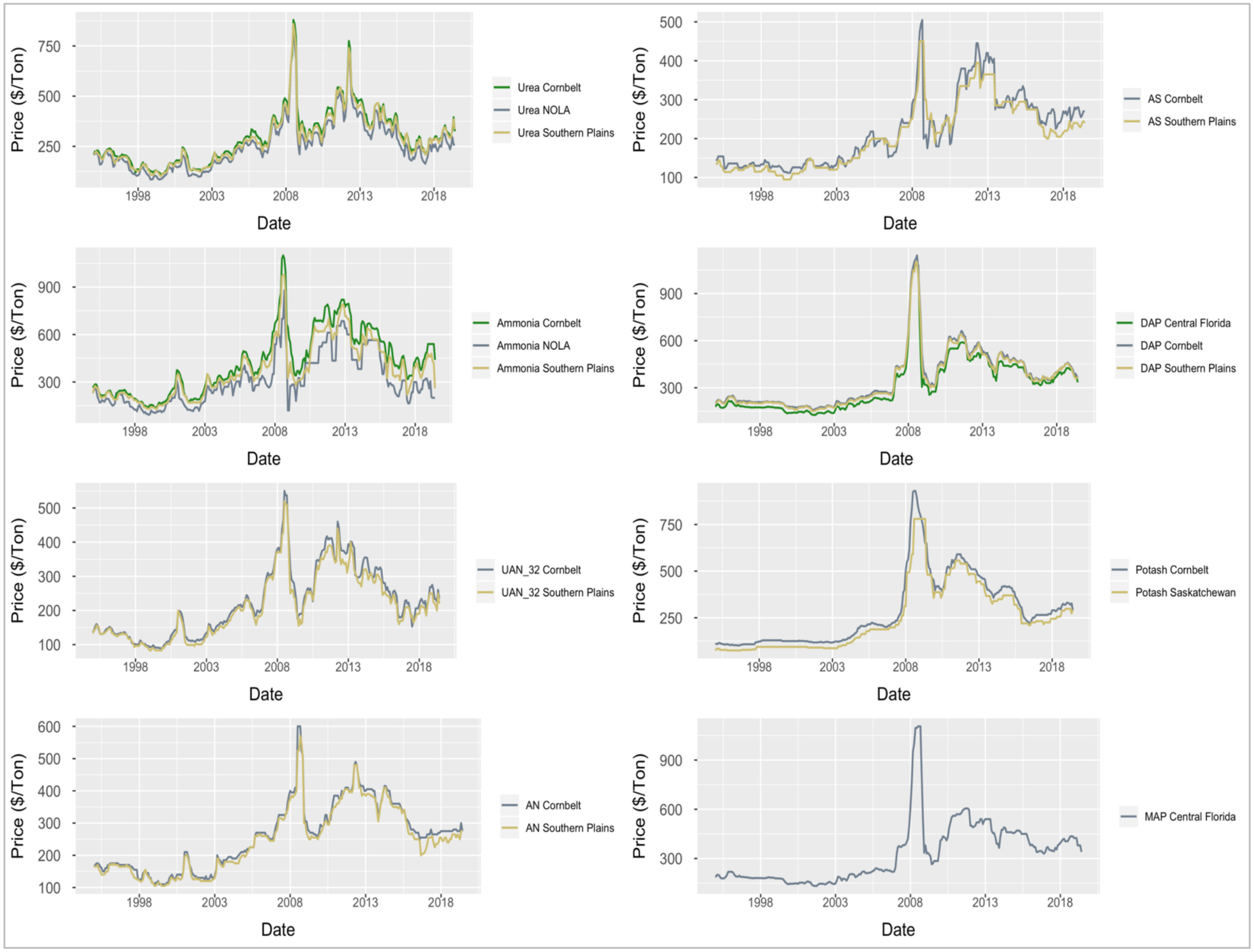

Figure 3. 4 Monthly Wholesale Fertilizer Prices (1995-2019)

Each of the variables selected must be tested for non-stationarity to avoid spurious regression results. The Dickey-Fuller test is one of the most common tests for detecting stationarity issues. The assumed generated equation of the data is as follows:

$$y_t = \alpha + \beta\, y_{t-1} + \varepsilon_t$$

where α is a linear constant term, β is the estimated slope parameter for y_t, y_{t-1} is the lagged value of y_t, and ε_t is the error term. The Dickey-Fuller test generates an OLS equation and tests the null hypothesis that β=1, which would indicate that the variable was non-stationary. The regression equation uses differenced values of the independent variable. The equation is as follows:

$$\Delta y_t = a_0 + a_1 y_{t-1} + u_t$$

where $\Delta y_t = y_t - y_{t-1}$, a_0 is a linear constant term, $a_1 = (\beta-1)$, and u_t is an error term. This model can be estimated and tested for a unit root: $a_1 = 0$. If a unit root is present, the data is considered non-stationary. The test is computed over the residual term, therefore cannot use the standard t-test to provide critical values. Alternatively, the test has its own distribution and statistical tests known as the Dickey-Fuller table. The Dickey-Fuller test was performed on the data and recorded in Table 2 (Dickey and Fuller 1978). The p-value was insignificant at the 5 percent level for all variables except Ammonium Sulfate, indicating that the data is non-stationary. First differences found that the data was stationary at one lag.

The current thesis employs vector autoregression to model the selected variables. Vector autoregression (VAR), is a widely used multivariate time series approach. VAR models are beneficial for forecasting and simulating real world economies. In this approach, selected variables are included in one equation as dependent variables. In its reduced form, lagged values of the dependent variables are included on the right-hand side of the equation. A VAR model can be expressed as:

$$X_t = \sum_{i=1}^{k} \beta_i X_{t-i} + \alpha + u_i$$

where X_t is an (nx1) vector of dependent time series variables, α is a vector of intercepts, β_i is an (nx1) vector of coefficient matrices, X_{t-i} is the vector of lagged dependent variables, and u_i is an (nx1) vector of zero mean error terms, or white noise (Awokuse and Bessler 2002; Sims 1980). A VAR model was selected for the current thesis because of the individualistic nature of the markets included as variables. For this reason, the variables in a VAR model are considered dependent variables, correlated together by their own lagged values and an error term.

Prior to estimation, a lag selection test is performed to find the most parsimonious model. The Bayesian Information Criteria (BIC) is used. BIC is formally defined as:

$$\mathrm{BIC} = \ln(n)\, k - 2\ln(\hat{L})$$

where n is the number of data observations, k is the number of parameters estimated by the model, and $\hat{L}$ is the maximized value of the likelihood function. BIC estimates the probability that the minimized model is true. It imposes a strict penalty term for the number of parameters in the model so as to prevent overfitting. (Schwartz 1978).

Variables are then selected for the forecasting models. The fertilizer product that will be forecasted is considered the primary variable. Explanatory variables are added individually and included in the model if the adjusted R^2 of the primary variable increases by 5 percent or more. The explanatory variables considered include the United States corn price (Corn), crude oil price per barrel (CrudeOil), natural gas price per British thermal unit (NatGas), exchange rates for Canada, Russia, and Morocco, and the port prices for New Orleans, Central Florida, and Saskatchewan. The lag and variable selection process establishes the model that will be used for forecasting. Results for these models are discussed in Chapter IV.

An out-of-sample forecast is evaluated prior to estimating periods into the future. The out-of-sample model estimates parameters from January 1995 to December 2010. The variables and lag length of the out-of-sample model were chosen during the variable and lag selection processes. According to Kim and Brorsen (2017), structural change is frequently observed within agricultural production and time series data. To account for these potential changes, a rolling window is used to generate the out-of-sample forecasts. The window is set to extend in six-month increments beginning in December 2010. This approach yields a June and December forecast for each estimated year. The window will estimate a new model and six month forecast until the end of the dataset (June 2019). Because the data are differenced, the forecast results are estimated price changes from one year to the next. The six forecast observations are summed and added to the actual per ton fertilizer price to calculate a six month forecast. So, for a June 2011 forecast, the summed observations will be added to the December 2010 price. The out-of-sample forecasts are compared with the actual observed data using mean absolute percentage error (MAPE). The naïve forecast is calculated by lagging the observed price. Because the out-of-sample forecasts are six month intervals, the naïve forecast is the lagged six month observed price from December 2010 to June 2019. The MAPE of the naïve forecast is compared with the VAR model to test the performance of the forecasts.

One of the primary goals of this thesis is to discover if there is an optimal time to make fertilizer purchases. Three purchasing strategies are explored. "Purchase Now" suggests that farmers should look to buy fertilizer ahead of time. The "Purchase Now" strategy is made up of the naïve forecast values. "Purchase Later" recommends that farmers wait until the price drops before purchasing product and is the observed prices of June and December from 2011 to 2019. A conditional statement is programmed into the model to develop an optimized purchase strategy, "Optimized Purchase". The statement simulates what a farmer should do to minimize costs by observing the generated six month forecast. If the forecast is greater than the "Purchase Now" strategy, then the "Purchase Now" price is chosen. Similarly, if the forecast is less than the "Purchase Now" strategy, then the farmer should choose the "Purchase Later" price. These purchasing strategies will tell if there are seasonal changes between different times of the year because the purchasing strategies correspond to either June or December. Therefore, a statistical t-test is then calculated at the 5 percent level to determine if there is any significant difference between the purchasing strategies. Significant differences in these prices may provide evidence of seasonal changes, thus providing farmers with an idea of how to make purchasing decisions. Results are discussed in Chapter IV.

The final objective of this study was to forecast a retail price for the Corn Belt and Southern Plains region. The out-of-sample model is used to forecast 12 months into the future using the entire dataset (January 1995 to June 2019). The retail price wedge for the Corn Belt and Southern Plains region are added to the forecast to reflect retail prices for the Corn Belt region and the state of Texas.

CHAPTER IV

RESULTS AND DISCUSSION

The models were estimated and analyzed for each of the fertilizer products for the Corn Belt and Southern Plains regions. The model results are interpreted and discussed in this chapter.

Urea Corn Belt

The variable selection process was used to select variables for the Urea Corn Belt model. The Bayesian Information Criteria (BIC) suggested that the most parsimonious model required three lags. The adjusted R^2 was calculated to be 57.4 percent. The coefficients of the selected variables are found in Table A-1. Urea Corn Belt had a negative sign; and crude oil, natural gas, and New Orleans urea had positive signs and were significant. Ammonia from the port of New Orleans had a negative sign and was only significant for the first two lags.

The model was forecasted for each rolling window. Forecasted and observed wholesale urea prices are in Figure 4.1. The mean absolute percentage error (MAPE) was calculated at 15.93 percent. The naïve forecast was calculated and performed better than the VAR model with a MAPE of 14.7. The average cost of buying fertilizer early was $374 per ton, $367 for waiting, and $368 for the cost minimizing, forecast based price. The results of the t-test were insignificant, indicating that there is not much price difference between purchasing fertilizer early or waiting until planting. The retail price forecast is expected to increase slightly before flattening out (Figure 4.2).

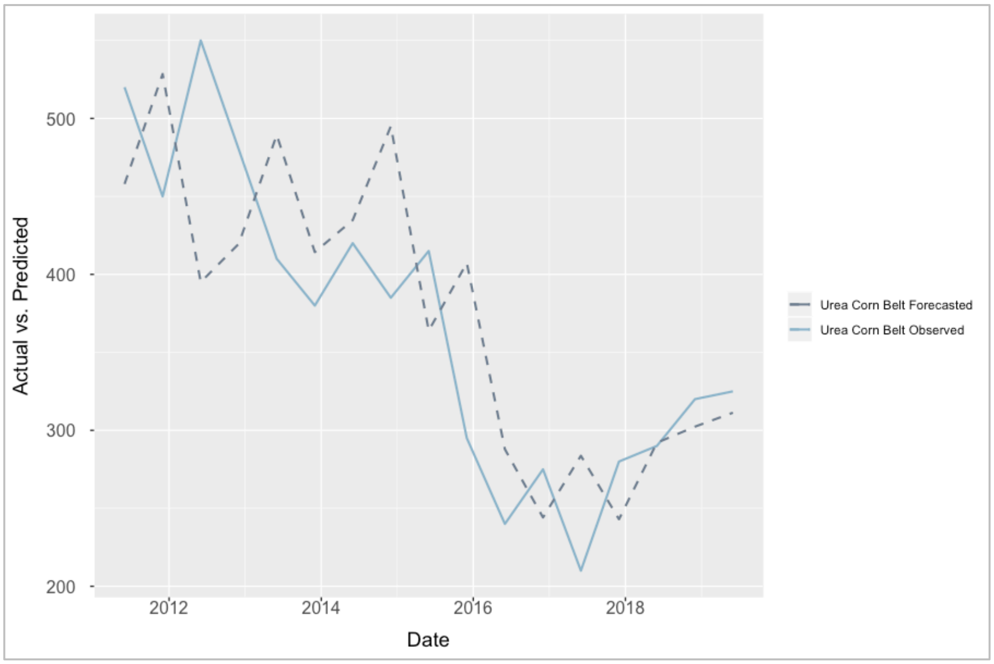

Figure 4. 1. Urea Corn Belt Observed and Predicted

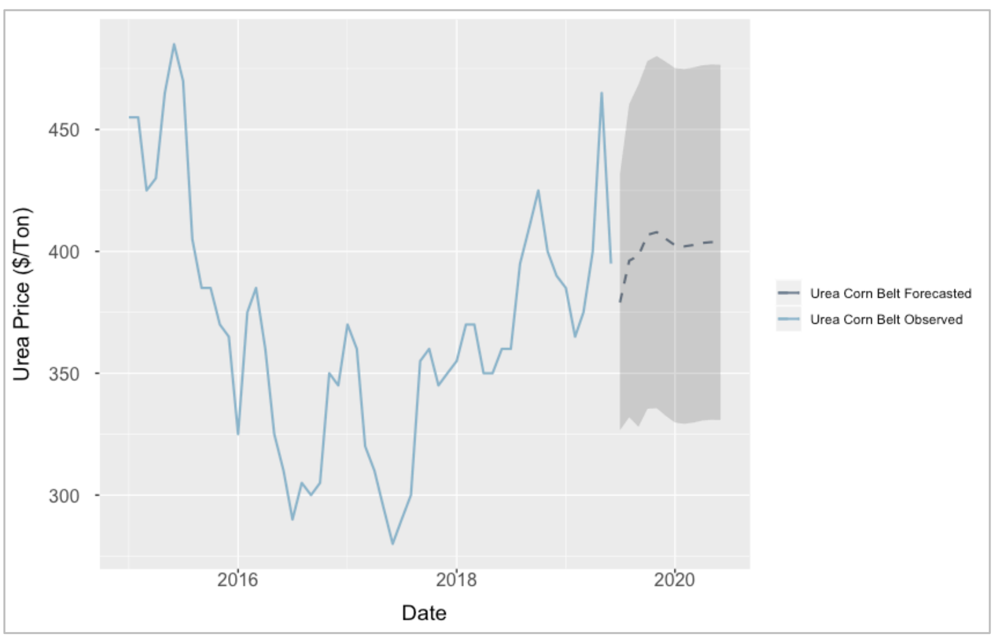

Figure 4. 2. Urea Corn Belt Retail Forecast

Urea Southern Plains

Variables for the model were selected and the BIC criterion suggested three lags as the most effective model. The adjusted R^2 for the Urea Southern Plains equation was 59.9. Crude Oil was positive and significant, but decreased in p-value with each lag until becoming insignificant at the third lag. Transportation may not drive urea price in the Southern Plains region due to close proximity to urea production plants. Natural gas was significant and had a positive sign. The New Orleans ammonia and Corn Belt urea prices had negative signs. The estimated coefficients are found in Table A-2 in Appendix A.

The model was forecasted every six months and the MAPE was calculated at 15.4 (Figure B-1). The naïve forecast performed as well as the VAR model with a MAPE of 15.5 percent. The average cost of purchasing fertilizer ahead of time was $358 per ton, while the cost of purchasing later was $354. The forecast based price combining the two optimized purchasing strategies was $345. The results of the t-test were insignificant, indicating that there is not much price variability from month to month. The retail price forecast for Texas urea prices is projected to decrease from early 2019 before recovering in the later months (Figure B-2).

Anhydrous Ammonia Corn Belt

The BIC criterion suggested three lags as the most effective model. Adjusted R^2 for the ammonia Corn Belt model was 59.9 percent. Lagged ammonia Corn Belt price was significant for the first two lags and had a positive sign. New Orleans urea and crude oil had the expected positive signs and were significant. Corn Belt urea was significant at the third lag and had a negative sign. These estimated coefficients are found in Table A-3.

The six-month forecasts were reported in Figure B-3. The MAPE was calculated at 18 percent, while the MAPE of the naïve forecast was 14.3 percent. The average cost of buying fertilizer ahead of time was $574 and buying when needed was $559 per ton. The optimized purchasing strategy price was $571. The t-test between purchasing strategies were insignificant at the 5 percent level, indicating that there is no significant difference between June and December. The retail Corn Belt price is expected to decrease before recovering slightly in 2020 (Figure B-4).

Anhydrous Ammonia Southern Plains

The model for anhydrous ammonia in the Southern Plains region suggested one lag for the most parsimonious model. The adjusted R^2 for the ammonia Southern Plains model was 61.9 percent. Urea at the port of New Orleans and crude oil were significant and positive. Lagged Southern Plains ammonia was insignificant. Both ammonia prices (Corn Belt and Southern Plains) are insignificant at the first lag. These model results were reported in Table A-4. The estimated parameters were used to forecast the wholesale ammonia price (Figure B-5).

The MAPE of the VAR model was estimated at 23.8. The naïve forecast MAPE showed that it was more accurate than the VAR model at 22.3 percent. The average cost of buying ahead of time was $494 and $473 for waiting to purchase fertilizer. The mean of the optimized strategy was $483. There was no significant difference in the means from purchasing fertilizer early versus waiting until later. Ammonia price is not expected to change much on a month to month level. The price wedge was added to reflect retail prices and is expected to remain constant from 2019 onward (Figure B-6).

Ammonium Nitrate Corn Belt

The lag selection process suggested three lags and the Adjusted R^2 was 59.9 percent. Crude Oil and urea at the port of New Orleans were significant and positive for the second and third lag. Corn was also a significant variable for the first and third lag. Lagged ammonium nitrate price was significant for the second and third lag and had a negative sign (Table A-5).

The estimated parameters were used to estimate the rolling window forecasts (Figure B-7). The MAPE was 9 percent, but was outperformed by the naïve forecast (8 percent). The mean of purchasing the fertilizer early is $342 and $336 for waiting later. The combined purchasing strategy was $335. The difference between each was six dollars, indicating that there is no significant difference between purchasing strategies. The retail price shows ammonium nitrate price increasing before leveling out in 2020 (Figure B-8).

Ammonium Nitrate Southern Plains

The variable selection process chooses two lags. Parameters are estimated and adjusted R^2 was calculated to be 66.3 percent (Table A-6). Lagged ammonium nitrate price had a negative sign. New Orleans urea, crude oil, and corn had positive signs and were significant.

The rolling windows are forecasted and yield a MAPE of 12.4 percent (Figure B-9). Naïve MAPE is slightly better at 11.2 percent. The mean cost of buying early was $325, $320 for waiting, and $319 for the optimized purchasing strategy. The t-test confirmed this observation, as the purchasing strategies were insignificant. The retail forecast showed that ammonium nitrate price is expected to increase from late 2019 until 2020 (Figure B-10).

Ammonium Sulfate Corn Belt

Five lags were selected for the model. The estimated coefficients are found in Table A-7. The adjusted R^2 was 42.3 percent. Lagged Corn Belt ammonium sulfate was negative and significant for the second and fifth lag. Corn Belt urea and Corn Belt ammonia were selected as explanatory variables and each had positive and negative impacts on ammonium sulfate at various lag lengths. Forecasts are observed in Figure B-11.

The forecasts yielded a MAPE of 9.8 percent, while the naïve forecast MAPE was calculated at 8.5 percent. The average price for purchasing fertilizer early was \$317 and \$316 for waiting until planting. The mean of the forecast based prices were slightly higher at \$322. The results of the t-test showed that there is no significant difference in the means of the purchasing strategies. Retail price forecasts followed a positive trend in the Corn Belt region but are expected to decrease in the next six-month period (Figure B-12).

Ammonium Sulfate Southern Plains

Three lags were chosen and the adjusted R^2 is 68.5 percent. The coefficients for Southern Plains ammonium sulfate and the selected explanatory variables are found in Table A-8. Lagged ammonium sulfate had a negative sign. Southern Plains urea positively influenced ammonium sulfate prices. Southern plains ammonia had a negative sign for the first lag and was positive for the second. The Southern Plains region is where much of the ammonium sulfate is produced, as the Coastal Bend of Texas is rich in sulfur deposits and is close in proximity to ammonia producing areas. Forecasts are generated and observed in Figure B-13.

The forecast MAPE was 9.3 percent and is outperformed by the naïve forecast (8.7 percent). The mean of purchasing fertilizer now was $286 per ton and $284 for waiting. The forecast based price analysis was $281. The t-test results supported the expectation that there was no significant difference between these means. The retail price in Texas has experienced some variability in prices. The results of the next six month window show that prices will decrease before leveling out in January 2020 (Figure B-14).

<u>Urea Ammonium Nitrate Corn Belt</u>

Three lags were selected as the most parsimonious model. The adjusted R^2 was calculated at 56.1 percent. Lagged UAN Corn Belt Price was significant at the second lag and had a negative sign. Natural gas had the expected positive sign on the coefficient, which was expected because it is an input for producing ammonia. New Orleans Urea also had a positive sign (Table A-9).

Observed and predicted values are found in Figure B-15. The MAPE was 11.2 percent. The naïve forecast performed slightly better with a MAPE of 11.2 percent. The average price of purchasing fertilizer early was $303. Waiting six months to purchase fertilizer was $296. There was not a significant difference in the means between the two strategies and is confirmed by the insignificant t-test results. Nevertheless, the optimized price based on the forecast was $302. The retail price of UAN is expected to remain constant for the next few periods (Figure B-16).

Urea Ammonium Nitrate Southern Plains

The BIC criterion suggested two lags for the most effective model. The adjusted R^2 is 61.1 percent. New Orleans urea and natural gas both have positive signs. Lagged Southern Plains UAN prices were significant with a positive and negative sign for the first and second lag respectively (Table A-10).

Forecasts were calculated for the six month intervals (Figure B-17). The MAPE of the VAR model was 10.6 percent. The naïve forecast MAPE was calculated at 9 percent, indicating that the naïve forecast was more accurate. The mean cost of purchasing fertilizer early was $270 per ton while the mean cost for waiting would cost $264. The optimized forecast based price was $264. The t-test shows that there was not much of a difference in the means of purchasing fertilizer now versus waiting, as the test was insignificant. The retail price for Texas has followed a positive trend in the last few periods. The forecast shows that the retail price of UAN will remain constant in the next period (Figure B-18).

Diammonium Phosphate (DAP) Corn Belt

Three lags were chosen. The adjusted R^2 was 74.7 percent. Crude oil had the expected positive sign for lags that were significant. Lagged DAP prices from the port of Central Florida were negative at the third lag. Lagged DAP Corn Belt prices were positive for the first and third lag and negative at the second (Table A-11).

The estimated coefficients were used to generate the rolling window forecasts (Figure B-19). The MAPE was 10.5 percent. The naïve forecast MAPE was 9.1 percent and therefore more accurate. The cost of purchasing fertilizer early was $469 per ton while waiting until later was $455. The t-test to determine whether there was any price movements between months was insignificant. The optimized purchase strategy price was $455. The t-test between purchase strategies was not significant at the 5 percent level. The retail Corn Belt price is expected to experience a slight decrease before flattening out (Figure B-20)

Diammonium Phosphate (DAP) Southern Plains

The BIC criterion suggests three lags. The adjusted R^2 of the model was 69.9 percent. Crude oil had a positive sign and was significant for all three lags. Central Florida DAP had a positive and negative sign for the first and third lags respectively. The second lag was insignificant. Lagged Southern Plains DAP price was significant for the first lag and had a positive sign. The estimated coefficients were recorded in Table A-12. Forecasts are calculated every six months (Figure B-21).

The MAPE was 10.3 percent for the VAR model and the naïve model had a MAPE of 8.2 percent. The mean cost of purchasing fertilizer early was $459 per ton and $445 for purchasing later. The mean of the optimized forecast price was $440. There was no significant difference between purchasing strategies. The retail forecast for the state of Texas has experienced some variability in the last two periods. Prices are expected to decrease slightly before flattening out (Figure B-22).

Monoammonium Phosphate (MAP) Central Florida

The model selection process chose the appropriate variables and one lag for the model. The adjusted R^2 was 46.3 percent. Crude oil was significant and had a positive sign. The exchange rate for Moroccan to United States currency was significant and had a negative sign. This was not the expected result because it is assumed that if an exporting country's exchange rate increased in that country, it would cause price to increase for that good in the importing country. Lagged Central Florida MAP price had a positive sign (Table A-13).

The VAR model was forecasted and the MAPE is 8.6 percent (Figure B-23). The naïve forecast was 9.3 percent, suggesting that the VAR model was more accurate. The price of buying fertilizer ahead of time was \$448 per ton and \$435 for waiting until it is needed. The optimized purchase price was \$434. The t-test results were insignificant, so farmers would not save much money by choosing one purchasing strategy over another. The retail price forecast for MAP is expected to decrease slightly in the next period (Figure B-24).

<u>Potash Corn Belt</u>

One lag was chosen for the most effective model. The adjusted R^2 was 50.8 percent. Crude oil had a positive sign, which is reasonable as much of the potash fertilizer is transported from Canada to the United States. The potash price from the port of Saskatchewan was positive as well. Corn was included in the model and had the expected positive sign. This was no surprise because as corn price increases, farmers are expected to apply more potash fertilizer. Many farmers, particularly in Texas, have opted not to use potash because it is expensive and is found naturally in many soil types (Table A-14).

The observed and predicted values were graphed in Figure B-25. The MAPE of the VAR model was 7.6 percent. The naïve model did not perform as well at 9.4 percent, indicating that the VAR model provided a more accurate forecast. The average cost of buying fertilizer early was \$390 per ton and \$377 for waiting. The optimized forecast based price was \$372. There was no significant difference in the means of the purchasing strategies, as the t-test was insignificant. The retail price forecast for the Corn Belt has decreased since 2015, but has followed an increasing trend since that time. The expectation is that prices will decrease in the next six months due to depressed commodity markets (Figure B-26).

Discussion

Many of the fertilizer products followed the same price trends from month to month. As ammonia is the major input for most products, this is a reasonable result. Crude oil was significant and had a positive impact on most fertilizer products in the dataset. As stated in previous chapters, this was expected due to the logistics required to transport fertilizer. Natural gas was an important variable for the urea and UAN fertilizers for the Corn Belt and Southern Plains. Surprisingly, natural gas was not significant for either ammonia model. Port prices out of New Orleans, Central Florida, and Saskatchewan were found to provide good measures of fit for the models. Corn was a significant factor for generally more expensive fertilizers, such as ammonium nitrate and potash. One plausible explanation is that farmers could be becoming more selective of which fertilizer products they apply during times where commodity markets are low and increasing the use of these fertilizers when prices increase. Exchange rates were insignificant other than the Central Florida MAP model which included the Moroccan rate. This was an expected result because the impact of exchange rates would have been accounted for at the processing level (as evidenced by the Central Florida MAP price). Even then, because the fertilizer processing industry is so consolidated, the exchange rates may not have much of an impact.

The averages of the three purchasing strategies are found in Table 4.2. The average mean absolute percent error (MAPE) of the out-of-sample and naïve forecasts can be found in Table 4.3. The t-tests to find whether there was any statistical difference in the means of buying in December versus June were insignificant at the 5 percent level for all models. Different combinations of months were tested during times that farmers are expected to purchase fertilizer (December versus February, July versus January, etc.) with similar insignificant results. This was surprising because observing the graphed prices from January 2017 to June 2019 shows that there could be some seasonality to the data that would cause farmers to benefit from purchasing fertilizer ahead of time (or waiting) (Figure 4.3). Upon further examination, however, either the price changes do not increase enough to be advantageous to the farmer, or the variability in the data does not happen at the same times each year, making it difficult to predict the cost minimizing purchasing strategy. Because fertilizer is used in all production regions and applied at least twice a year (at pre-plant and planting time), demand stays relatively high all year. In Texas alone, the optimal time to apply fertilizer is different for the Panhandle and the Gulf Coast. Additionally, some producers will have cover crops of commodities that require different levels of fertilizers at different times of the year.

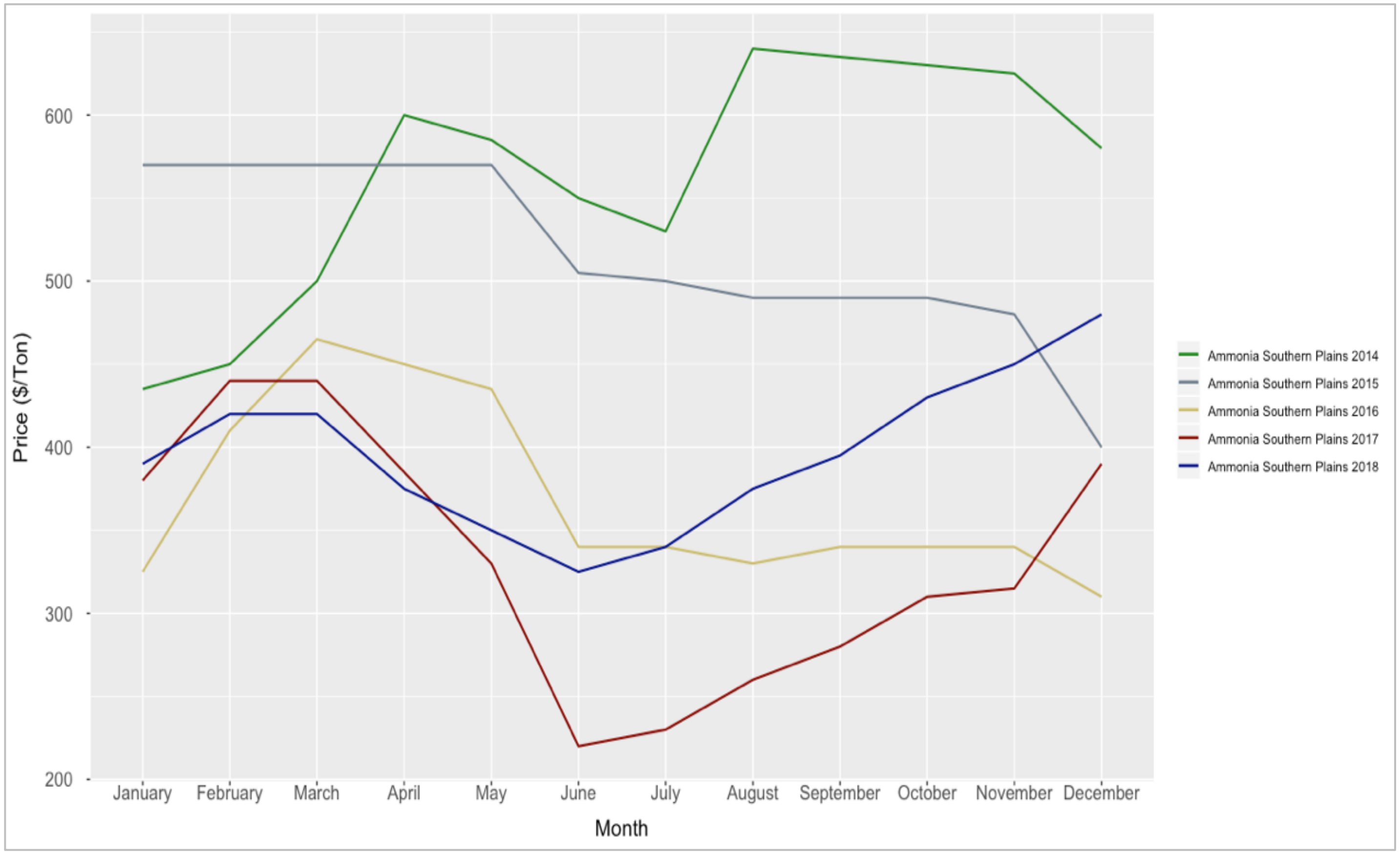

Figure 4. 3. Ammonia Southern Plains Seasonal Differences

Table 4. 1: Forecast Results and Decision Analysis

	Purchase Now	Forecast	Purchase Later	Optimized Purchase Strategy
Urea Corn Belt	374	375	367	374
Urea Southern Plains	358	365	354	358
Ammonia Corn Belt	574	565	559	559
Ammonia Southern Plains	494	485	473	473
AN Corn Belt	342	339	336	336
AN Southern Plains	325	323	320	320
AS Corn Belt	317	311	316	316
AS Southern Plains	286	278	284	284
UAN Corn Belt	303	304	296	303
UAN Southern Plains	270	281	264	270
DAP Corn Belt	469	444	455	455
DAP Southern Plains	459	441	445	445
MAP Central Florida	448	439	435	435
Potash Corn Belt	390	386	377	377

Table 4. 2: MAPE of Out-of Sample and Naïve Forecasts

	MAPE of VAR	MAPE of Naïve Forecast
Urea Corn Belt	15.9	14.7
Urea Southern Plains	15.4	15.5
Ammonia Corn Belt	18.0	14.3
Ammonia Southern Plains	23.8	22.3
AN Corn Belt	9.0	8.0
AN Southern Plains	12.4	11.2
AS Corn Belt	9.8	8.5
AS Southern Plains	9.3	8.7
UAN Corn Belt	11.2	10.0
UAN Southern Plains	10.6	9.0
DAP Corn Belt	10.5	9.1
DAP Southern Plains	10.3	8.2
MAP Central Florida	8.6	9.3
Potash Corn Belt	7.6	9.4

CHAPTER V

CONCLUSIONS

The three objectives of this research were to develop forecasting models of average wholesale prices for nitrogen, phosphorus, and potassium fertilizers, conduct a comparative cost analysis between purchasing fertilizer in advance versus buying it at the time of need, and develop a Texas specific price forecast. The decision to book fertilizer in advance verses buying when needed is a business management issue for many farmers. If farmers have a tool that will help them gauge where prices are going, they will be more likely to take advantage of cost savings from buying fertilizer at the optimal time. Lenders, landlords, and those associated with farming operations should also benefit from knowing price trends in the fertilizer industry.

Literature Review and Methodology

The most successful forecasting models from previous studies used time series models (Vroomen 1991, Kim and Brorsen 2017). The proposed project used vector autoregression because of the many variables that are believed to effect fertilizer prices. Multiple variables were considered and chosen by a variable selection process. The use of exchange rates as a forecasting variable were not found in previous studies but were included because much of the supply of fertilizer is concentrated in certain areas of the world (particularly phosphorus). The top U.S. fertilizer trade partners are Canada, Morocco, and Russia. Monthly data was used to provide a better understanding of seasonal trends in the fertilizer industry (Ibendahl 2017). Out-of-sample forecasts were determined for six month intervals and tested for forecast accuracy using mean absolute percent error. These models were compared with the mean absolute percent error of the naïve forecast. Three purchasing strategies, “Purchase Now”, “Purchase Later”, and “Optimized Purchase” were analyzed to see how often prices change from one six month interval to the next. A t-test was calculated between the “Purchase Now” and “Purchase Later” strategies that determine if prices change between June and December.

The available dataset includes the following fertilizer products for multiple production regions: anhydrous ammonia, ammonium nitrate, ammonium sulfate, diammonium phosphate, monoammonium phosphate (MAP), potassium chlorate (potash), urea ammonium nitrate (UAN), and urea. Two production regions (Corn Belt and Southern Plains) were modeled for each of these products to provide a comparison of fertilizer use between different areas in the U.S. The Corn Belt region includes Ohio, Indiana, Illinois, Iowa, Missouri, and Nebraska; the Southern Plains region collects prices from Texas, Oklahoma, Kansas, Colorado, and New Mexico. Henry Hub natural gas price was included as an explanatory variable in the model, as natural gas is an input for production of nitrogen fertilizer products. The national average corn price from the National Agricultural Statistics Service was included to see how fertilizer prices move with commodity markets. The West Texas Intermediate crude oil price was included to account for transportation expenses. AFPC panel members provided data for the retail price wedge for the Southern Plains region.

Results

Many of the fertilizer products followed the same price trend as anhydrous ammonia because almost all of the products contain it. Crude oil was significant and had a positive impact on most fertilizer products in the dataset. Natural gas was an important variable for the urea and UAN fertilizers for the Corn Belt and Southern Plains. Surprisingly, natural gas was not significant for either ammonia model. Port prices out of New Orleans, Central Florida, and Saskatchewan were found to improve adjusted R^2 the most. Corn was a significant factor for more expensive fertilizers, such as ammonium nitrate and potash. Exchange rates were insignificant other than the Central Florida MAP model, which included the Moroccan exchange rate. Phosphorus supply is limited to certain areas of the world relative to other fertilizer products, with 71 percent of the phosphorus reserves located in Morocco. The fact that this was the only significant exchange rate is a plausible outcome.

The average mean absolute percent error (MAPE) varied from 7 to 16 percent (Table 4.16). The t-tests to find whether there was any statistical difference among months were insignificant at the 5 percent level for all models. This was surprising because observing the graphed prices from January 2017 to June 2019 shows that there could be some seasonality to the data that could save farmers money if timed properly (Figure 4.29). One explanation for this result is that either the price changes do not increase enough to be advantageous to the farmer, or the variability in the data does not happen at the same times each year. Because fertilizer is used in all production regions and applied at least twice a year (at pre-plant and planting time), demand stays relatively high all year. In

Texas alone, the optimal time to apply fertilizer varies for the Panhandle and the Gulf Coast.

Additional Research Opportunities

The lack of variability between different months was very surprising, as there are annual seasonality trends that have been observed for many years. Using a different model other than Vector Autoregression could potentially provide those seasonal differences. One other approach that could lead to more accurate results is to use a more localized form of data. The Green Markets monthly prices are divided into regions (Corn Belt and Southern Plains). These regions are made up of many states that have different production practices (some even within the state i.e. Texas). This consolidated form of data may not have taken seasonal changes into account because the demand for fertilizer peaks at different times of the year in different areas.

The fertilizer industry remains a mystery to many researchers, lenders, and farmers alike. The business structure of processors, limited supplies of phosphorus, and exploring logistical bottlenecks are all potential areas of study that could answer some of these questions. Purchasing fertilizer prior to the end of the tax year is often used to manage taxes as well as take advantage of lower prices that sometimes occur before the end of the year. A study that would analyze tax savings of purchasing fertilizer could be another interesting project. As commodity markets continue to trend downward, providing tools for farmers to save money becomes of the utmost importance. This study lays the groundwork for future fertilizer research despite these surprising results.

REFERENCES

Achorn, F.P., and H.L. Balay. 1985. "Production, Marketing, and Use of Solid, Solution, and Suspension Fertilizers." In *Fertilizer Technology and Use*. Madison, WI: Soil Science Society of America, Inc. , pp. 483–502.

Awokuse, T.O., and D.A. Bessler. 2003. "Vector Autoregressions, Policy Analysis, and Directed Acyclic Graphs: An Application to the U.S. Economy." *Journal of Applied Economics* 6(1):1–24.

Babcock, Bruce A., and Gregory R. Pautsch. 1998. "Moving from Uniform to Variable Fertilizer Rates on Iowa Corn: Effects on Rates and Returns." *Journal of Agricultural and Resource Economics* 23(2): 385-400.

Baethgen, W.E., D.B. Taylor, and M.M. Alley. 1989. "Quadratic Programming Method for Determining Optimum Nitrogen Rates for Winter Wheat During Tillering." *Agronomy Journal* 81(4):557.

Bollman, K., P. Garcia, and S. Thompson. 2003. "What Killed the Diammonium Phosphate Futures Contract?" *Review of Agricultural Economics* 25(2):483–505.

Borlaug, Norman E., and Oddvar H. Aresvik. 1973. "The Green Revolution-An Approach to Agricultural Development and Some of its Economic Implications." *International Journal of Agrarian Affairs* 5(26): 385-403.

Carman, Hoy F. 1979. "The Demand for Nitrogen, Phosphorous and Potash Fertilizer Nutrients in the Western United States." *Western Journal of Agricultural Economics* 4(1): 23-31.

Cerrato, M.E., and A.M. Blackmer. 1990. "Comparison of Models for Describing; Corn Yield Response to Nitrogen Fertilizer." *Agronomy Journal* 82(1):138.

Cordell, D., J.-O. Drangert, and S. White. 2009. "The Story of Phosphorus: Global Food Security and Food for Thought." *Global Environmental Change* 19(2):292–305.

Dickey, D.A., and W.A. Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of the American Statistical Association* 74(366):427.

Evans, Lloyd T. 1980. "The Natural History of Crop Yield: A Combination of Improved Varieties of Crop Plants and Technological Innovations Continues to Increase Productivity, but the Highest Yields are Approaching Limits set by Biological Constraints." American Scientist 68(4): 388-397.

Forster, D. Lynn. 1985. “Optimum Phosphorus Fertilization”. Paper Presented at AAEA annual meeting, Ames, IA August 4-7.

Galbraith, Craig. 2010. “An Examination of Factors Influencing Fertilizer Price Adjustment”. Paper Presented at AAEA annual meeting, Denver, CO July 25-27.

Geman, H., and P.V. Eleuterio. 2013. “Investing in Fertilizer–Mining Companies in Times of Food Scarcity.” *Resources Policy* 38(4):470–480.

Godden, David P., and K. R. Helyar. 1980. "An Alternative Method for Deriving Optimal Fertilizer Rates." *Review of Marketing and Agricultural Economics* 48(2): 83-97.

Griliches, Z. 1958. “The Demand for Fertilizer: An Economic Interpretation of a Technical Change.” *Journal of Farm Economics* 40(3):591.

Gunjal, K.R., R.K. Roberts, and E.O. Heady. 1980. “Fertilizer Demand Functions for Five Crops in the United States.” *Journal of Agricultural and Applied Economics* 12(2):111–116.

Gyawu, E.A. 1984. *An Econometric analysis of the U.S. fertilizer industry*. Lexington, KY: University of Kentucky, College of Agriculture, Agricultural Experiment Station, Dept. of Agricultural Economics.

Heady, E.O., and M.H. Yeh. 1959. “National and Regional Demand Functions for Fertilizer.” *Journal of Farm Economics* 41(2):332.

Heffer, Patrick, and Michel Prud’homme. 2016. "Fertilizer Outlook 2016–2020." 84th IFA Annual Conference, Moscow, Russia.

Huang, Wen-yuan. 2007. *Impact of Rising Natural Gas Prices on US Ammonia Supply*. Washington DC: U.S. Department of Agriculture, ERS, August.

Huang, Wen-yuan. 2009. *Factors Contributing to the Recent Increase in US Fertilizer Prices, 2002-08*. Washington DC: U.S. Department of Agriculture, ERS, February.

Humber, J. 2014. "A Time Series Approach to Retrospective Merger Analysis: Evidence in the US Nitrogen Fertilizer Industry." Paper Presented at AAEA annual meeting, Minneapolis, MN July 27–29.

Ibach, D.B., and J.R. Adams. 1967. *Fertilizer Use in the United States by Crops and Areas, 1964 Estimates*. Washington, D.C.: U.S. Dept. of Agriculture, Economic Research Service and Statistical Reporting Service.

Ibendahl, Gregory. 2019. “Predicting Fertilizer Prices.” Ag Manager, Kansas State Extension, Feb.

Jokela, W.E. 1992. “Nitrogen Fertilizer and Dairy Manure Effects on Corn Yield and Soil Nitrate.” *Soil Science Society of America Journal* 56(1):148.

Joskow, P.L. 2013. “Natural Gas: From Shortages to Abundance in the United States.” *American Economic Review* 103(3):338–343.

Kansas State Extension. “Nutrient Planning Reference Guide: Managing Soil & Applied Nutrients.” Unpublished, Kansas State University.

Kenkel and Kim. 2009. "Optimal Cash Purchase Strategies to Reduce Fertilizer Price Risk." Paper Presented at SAEA annual meeting, Atlanta, GA January 31–February 3.

Kim, S.-W., and B.W. Brorsen. 2017. “Forecasting Urea Prices.” *Applied Economics* 49(49):4970–4981.

Lory, J.A., R. Massey, and B.C. Joern. 2008. “Using Manure as a Fertilizer for Crop Production.” In *Final report: Gulf Hypoxia and Local Water Quality Concerns Workshop*. St. Joseph, MI: American Society of Agricultural and Biological Engineers, pp. 105–116.

Ni, B., M. Liu, and S. Lü. 2009. “Multifunctional Slow-Release Urea Fertilizer from Ethylcellulose and Superabsorbent Coated Formulations.” *Chemical Engineering Journal* 155(3):892–898.

Pindyck, Robert S. 2004. "Volatility in Natural Gas and Oil Markets." *The Journal of Energy and Development 30(1): 1-19*

Plastina, Alejandro. 2018. "Estimated Costs of Crop Production in Iowa-2018." Iowa State Extension, January.

Raun, W.R., et al. 2002. “Improving Nitrogen Use Efficiency in Cereal Grain Production with Optical Sensing and Variable Rate Application.” *Agronomy Journal* 94(4):815.

Rausser, Gordon C., and Theo F. Moriak. 1970. "The Demand for Fertilizer, 1949-64: An Analysis of Coefficients from Periodic Cross Sections." *Agricultural Economics Research* 22(2): 45-56.

Roberts, R.K. 1986. “Plant Nutrient Demand Functions for Tennessee with Prices of Jointly Applied Nutrients.” *Journal of Agricultural and Applied Economics* 18(2):107–112.

Rogers, D.S., and J.T. Akridge. 1996. “Economic Impact of Storage and Handling Regulations on Retail Fertilizer and Pesticide Plants.” *Agribusiness* 12(4):327–337.

Russel, D.A., and G.G. Williams. 1977. “History of Chemical Fertilizer Development 1.” *Soil Science Society of America Journal* 41(2):260.

Salvagiotti, F., et al. 2008. “Nitrogen Uptake, Fixation and Response to Fertilizer N in Soybeans: A Review.” *Field Crops Research* 108(1):1–13.

Sawyer, J.E. 1994. “Concepts of Variable Rate Technology with Considerations for Fertilizer Application.” *Journal of Production Agriculture* 7(2):195.

Scharf, P.C., et al. 2005. “Field-Scale Variability in Optimal Nitrogen Fertilizer Rate for Corn.” *Agronomy Journal* 97(2):452.

Schnitkey, Gary. 2016. "Anhydrous Ammonia, Corn, and Natural Gas Prices Over Time." farmdoc daily, University of Illinois. No. 112, June.

Schwarz, G. 1978. “Estimating the Dimension of a Model.” *The Annals of Statistics* 6(2):461–464.

Shaviv, A. 2001. “Advances in Controlled-Release Fertilizers.” *Advances in Agronomy*:1–49.

Sims, C.A. 1980. “Macroeconomics and Reality.” *Econometrica* 48(1):1.

The Fertilizer Institute. 2018. “2018 State of the Fertilizer Industry.” State of the Fertilizer Industry.

Trenkel, M.E. 1997. *Controlled-release and Stabilized Fertilizers in Agriculture: Improving Fertilizer Use Efficiency*. Paris: IFA.

Twaddle, C. 1982. "Fertilizer and Energy." The Fertilizer Handbook.

U.S. Department of the Interior, U.S. Geological Survey. 2019. Mineral Commodity Summaries 2019. Washington DC, February.

Vroomen, H. 1991. “A Short-Run Forecasting Model for Nitrogen Fertilizer Prices.” *Agribusiness* 7(6):515–522.

Wollenhaupt, N.C., R.P. Wolkowski, and M.K. Clayton. 1994. “Mapping Soil Test Phosphorus and Potassium for Variable-Rate Fertilizer Application.” *Journal of Production Agriculture* 7(4):441.

Wu, L., M. Liu, and R. Liang. 2008. "Preparation and Properties of a Double-Coated Slow-Release NPK Compound Fertilizer with Superabsorbent and Water-Retention." *Bioresource Technology* 99(3):547–554.

APPENDIX A

PARAMETER ESIMTATION OF FERTILIZER PRODUCTS

Table A-1: Urea Corn Belt Model

	Dependent variable:				
	y				
	Urea Corn Belt	Urea NOLA	Crude Oil	Natural Gas	Ammonia NOLA
	(1)	(2)	(3)	(4)	(5)
Urea_Cornbelt.l1	-0.428^{***}	-0.18	-0.014	-0.006	-0.568^{***}
Urea_NOLA.l1	0.517^{***}	0.338^{**}	0.037	0.005	0.333^{*}
CrudeOil.l1	1.128^{***}	1.375^{***}	0.129	0.028^{*}	1.580^{***}
NatGas.l1	5.762^{***}	5.858^{**}	0.042	-0.07	8.003^{***}
AA_NOLA.l1	-0.235^{***}	-0.192^{***}	0.009	0.001	-0.022
Urea_Cornbelt.l2	-0.372^{***}	-0.213	-0.007	-0.001	0.884^{***}
Urea_NOLA.l2	0.438^{***}	0.206	0.007	0.002	0.095
CrudeOil.l2	1.225^{***}	1.512^{***}	0.134	0.01	-0.787
NatGas.l2	8.637^{***}	6.771^{***}	-0.622	-0.027	4.21
Urea_Cornbelt.l3	-0.472^{***}	-0.444^{***}	-0.029	0.002	-0.161
Urea_NOLA.l3	0.380^{***}	0.041	-0.026	-0.007	0.011
CrudeOil.l3	0.904^{**}	0.655	0.147^{*}	0.01	2.964^{***}
NatGas.l3	6.227^{***}	5.977^{**}	0.189	-0.049	1.151
Observations	188	188	188	188	188
Adjusted R^2	0.574	0.519	0.116	0.016	0.557
Residual Std. Error (df = 173)	23.095	26.087	4.836	0.873	33.823
F Statistic (df = 15; 173)	17.855^{***}	14.506^{***}	2.653^{***}	1.2	16.788^{***}
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A-2: Urea Southern Plains Model

	Dependent variable:				
	y				
	Urea Southern Plains	Crude Oil	AA NOLA	Natural Gas	Urea Corn Belt
	(1)	(2)	(3)	(4)	(5)
Urea_SP.l1	0.41**	0.02	0.52**	0.002	0.78***
CrudeOil.l1	1.46***	0.15*	1.51***	0.03**	1.05***
AA_NOLA.l1	-0.21***	0.01	-0.01	0.001	-0.22***
NatGas.l1	7.58***	0.13	8.55***	-0.06	7.28***
CrudeOil.l2	1.43***	0.12	-0.75	0.01	1.30***
NatGas.l2	7.97***	-0.57	3.38	-0.03	8.49***
Urea_SP.l3	0.39**	0.03	0.07	-0.002	0.64***
NatGas.l3	6.32***	0.22	0.54	-0.05	5.68***
Urea_Cornbelt.l3	-0.78***	-0.09**	-0.22	-0.002	-0.76***
Observations	188	188	188	188	188
Adjusted R^2	0.6	0.11	0.56	-0.001	0.59
Residual Std. Error (df = 173)	23.43	4.85	33.55	0.88	22.74
F Statistic (df = 15; 173)	19.68***	2.57***	17.25***	0.99	18.77***
Note:					*p<0.1; **p<0.05; ***p<0.01

Table A-3: Ammonia Corn Belt Model

	Dependent variable:			
	y			
	AA Corn Belt	Urea NOLA	Urea Corn Belt	Crude Oil
	(1)	(2)	(3)	(4)
Urea_NOLA.l1	0.450***	0.447***	0.652***	0.037
CrudeOil.l1	1.962***	1.587***	1.386***	0.109
AA_Cornbelt.l2	0.235***	0.253***	0.287***	-0.002
CrudeOil.l2	0.810*	1.866***	1.385***	0.178*
AA_Cornbelt.l3	0.219***	0.087	0.051	0.006
Urea_Cornbelt.l3	-0.355**	-0.818***	-0.921***	-0.005
Observations	188	188	188	188
Adjusted R^2	0.599	0.462	0.501	0.113
Residual Std. Error (df = 176)	24.773	27.569	24.988	4.846
F Statistic (df = 12; 176)	24.390***	14.478***	16.715***	2.995***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A-4: Ammonia Southern Plains Model

	Dependent variable:		
	y		
	AA Southern Plains	Urea NOLA	Crude Oil
	(1)	(2)	(3)
Urea_NOLA.l1	0.725***	0.365***	0.030**
CrudeOil.l1	1.485***	1.728***	0.158*
Observations	190	190	190
Adjusted R^2	0.619	0.204	0.087
Residual Std. Error (df = 187)	25.891	33.380	4.890
F Statistic (df = 3; 187)	104.105***	17.194***	7.063***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table A-5: Ammonium Nitrate Corn Belt

	Dependent variable:			
	y			
	AN Corn Belt	Urea NOLA	Crude Oil	Corn
	(1)	(2)	(3)	(4)
AN_Cornbelt.l1	-0.373***	-0.285*	-0.013	0.0005
Urea_NOLA.l1	0.005	0.241***	0.019	-0.0004
CrudeOil.l1	0.248	0.763	0.077	-0.004
Corn.l1	16.670**	38.535***	5.023**	0.540***
AN_Cornbelt.l2	-0.151**	0.089	-0.012	0.001*
Urea_NOLA.l2	0.317***	-0.088	-0.01	-0.0001
CrudeOil.l2	1.066***	2.036***	0.164*	0.004
Urea_NOLA.l3	0.128**	-0.300***	-0.014	-0.0004
CrudeOil.l3	0.937***	1.023**	0.167*	0.0002
Corn.l3	15.326**	32.206**	-2.351	-0.117
Observations	188	188	188	188
Adjusted R^2	0.599	0.52	0.164	0.263
Residual Std. Error (df = 176)	14.388	26.058	4.705	0.148
F Statistic (df = 12; 176)	24.362***	17.956***	4.072***	6.597***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A-6: Ammonium Nitrate Southern Plains

	Dependent variable:			
	y			
	AN Corn Belt	Urea NOLA	Crude Oil	Corn
	(1)	(2)	(3)	(4)
AN_SP.l1	-0.102**	-0.840***	-0.052***	-0.001**
Urea_NOLA.l1	-0.025	0.322***	0.027**	0.0001
CrudeOil.l1	0.214	1.066**	0.099	-0.004
Corn.l1	13.855**	27.960*	3.936	0.504***
AN_SP.l2	0.018	0.097	-0.004	0.001**
Urea_NOLA.l2	0.387***	-0.003	-0.003	0.0002
CrudeOil.l2	0.881***	1.711***	0.164*	0.003
Corn.l2	0.127	6.334	0.293	0.041
Observations	189	189	189	189
Adjusted R^2	0.663	0.358	0.125	0.246
Residual Std. Error (df = 181)	11.972	30.046	4.8	0.149
F Statistic (df = 8; 181)	47.390***	14.182***	4.386***	8.688***
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A-7: Ammonium Sulfate Corn Belt

	Dependent variable:		
	y		
	AS Corn Belt	AA Corn Belt	Urea Corn Belt
	(1)	(2)	(3)
Urea_Cornbelt.l1	0.241**	0.612***	0.372***
AS_Cornbelt.l2	-0.311***	-0.189	-0.216
AA_Cornbelt.l2	0.237***	0.072	0.098
AA_Cornbelt.l3	-0.338***	0.071	-0.118
Urea_Cornbelt.l3	-0.206**	0.02	-0.510***
AA_Cornbelt.l4	0.274***	0.096	0.344***
Urea_Cornbelt.l4	0.231**	-0.360***	-0.159
AS_Cornbelt.l5	-0.236**	-0.011	-0.017
Urea_Cornbelt.l5	-0.226**	0.181	-0.166
Observations	186	186	186
Adjusted R^2	0.423	0.534	0.302
Residual Std. Error (df = 171)	19.944	26.806	29.693
F Statistic (df = 15; 171)	10.089***	15.226***	6.361***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A-8: Ammonium Sulfate Southern Plains

	Dependent variable:		
	y		
	AS Southern Plains	Urea Southern Plains	Ammonia Southern Plains
	(1)	(2)	(3)
AS_SP.l1	-0.403***	0.680***	0.039
Urea_SP.l1	0.346***	0.521***	0.914***
AA_SP.l1	-0.073**	-0.204**	-0.133
AS_SP.l2	-0.133**	0.235	-0.027
Urea_SP.l2	0.103***	-0.103	0.195*
AA_SP.l2	0.066**	0.420***	0.108
AS_SP.l3	0.133**	-0.331*	-0.02
Urea_SP.l3	0.138***	-0.731***	-0.174*
Observations	188	188	188
Adjusted R^2	0.685	0.412	0.635
Residual Std. Error (df = 179)	8.984	28.362	25.494
F Statistic (df = 9; 179)	46.367***	15.610***	37.276***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A-9: UAN Corn Belt Model

	Dependent variable:		
	y		
	UAN Corn Belt	Urea NOLA	Natural Gas
	(1)	(2)	(3)
Urea_NOLA.l1	0.206***	0.394***	0.002
NatGas.l1	4.020***	8.611***	-0.009
UAN_Cornbelt.l2	0.250***	0.734***	0.006
Urea_NOLA.l2	0.092***	0.001	-0.0002
NatGas.l2	3.005***	8.194***	-0.003
NatGas.l3	1.822*	3.404	-0.064
Observations	188	188	188
Adjusted R^2	0.561	0.43	-0.038
Residual Std. Error (df = 179)	10.998	28.385	0.897
F Statistic (df = 9; 179)	27.656***	16.769***	0.232
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A-10: Ammonium Sulfate Southern Plains

	Dependent variable:		
	y		
	UAN Southern Plains	Urea NOLA	Natural Gas
	(1)	(2)	(3)
UAN_SP.l1	-0.272***	-0.971***	-0.008
Urea_NOLA.l1	0.270***	0.415***	0.002
NatGas.l1	5.614***	8.245***	0.001
UAN_SP.l2	0.124**	-0.239	0.006
Urea_NOLA.l2	0.193***	0.311***	0.0004
NatGas.l2	2.480**	12.293***	0.037
Observations	189	189	189
Adjusted R^2	0.611	0.306	-0.013
Residual Std. Error (df = 183)	11.218	31.246	0.883
F Statistic (df = 6; 183)	50.523***	14.880***	0.594
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A-11: DAP Corn Belt Model

	Dependent variable:		
	y		
	DAP Corn Belt	DAP Central Florida	Crude Oil
	(1)	(2)	(3)
DAP_Cornbelt.l1	1.017***	1.545***	0.013
DAP_Cornbelt.l2	-0.199*	0.457***	0.008
CrudeOil.l2	1.487***	1.325***	0.045
DAP_Cornbelt.l3	0.240***	0.324***	-0.018
DAP_CF.l3	-0.382***	-0.880***	-0.003
Observations	188	188	188
Adjusted R^2	0.747	0.688	0.084
Residual Std. Error (df = 179)	17.331	23.394	4.924
F Statistic (df = 9; 179)	62.519***	47.090***	2.923***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A-12: DAP Southern Plains

	Dependent variable:		
	y		
	DAP Southern Plains	DAP Central Florida	Crude Oil
	(1)	(2)	(3)
DAP_SP.l1	0.454***	1.066***	0.087***
DAP_CF.l1	0.208**	-0.171	-0.022
CrudeOil.l1	1.066***	1.800***	0.160**
CrudeOil.l2	0.799**	0.923**	0.047
DAP_CF.l3	-0.357***	-0.867***	-0.027
CrudeOil.l3	0.758**	1.003**	-0.039
Observations	188	188	188
Adjusted R^2	0.699	0.652	0.129
Residual Std. Error (df = 179)	19.106	24.728	4.802
F Statistic (df = 9; 179)	49.395***	40.059***	4.097***
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A-13: MAP Central Florida Model

	Dependent variable:		
	y		
	MAP Central Florida	Crude Oil	Morocco Exchange Rate
	(1)	(2)	(3)
MAP_CF.l1	0.539^{***}	0.031^{***}	0.0005
CrudeOil.l1	1.588^{***}	0.140^{*}	-0.006^{*}
Morocco.l1	-27.584^{**}	-0.572	0.044
Observations	190	190	190
Adjusted R^2	0.463	0.106	0.009
Residual Std. Error (df = 187)	30.49	4.839	0.212
F Statistic (df = 3; 187)	55.619^{***}	8.541^{***}	1.568
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A-14: Potash Corn Belt Model

	Dependent variable:			
	y			
	Potash Corn Belt	Crude Oil	Potash Saskatchewan	Corn
	(1)	(2)	(3)	(4)
POT_Cornbelt.l1	0.442***	0.014	0.901***	0.001**
CrudeOil.l1	1.005***	0.208***	-1.835***	-0.004*
POT_Canada.l1	0.221***	-0.023*	-0.045	0.0001
Corn.l1	15.175**	4.661**	-13.951	0.458***
Observations	190	190	190	190
Adjusted R^2	0.508	0.086	0.432	0.235
Residual Std. Error (df = 186)	15.327	4.894	22.289	0.15
F Statistic (df = 4; 186)	49.978***	5.462***	37.066***	15.597***
Note:				*p<0.1; **p<0.05; ***p<0.01

APPENDIX B

OBSERVED AND PREDICTED FORECASTS FOR FERTILIZER PRODUCTS

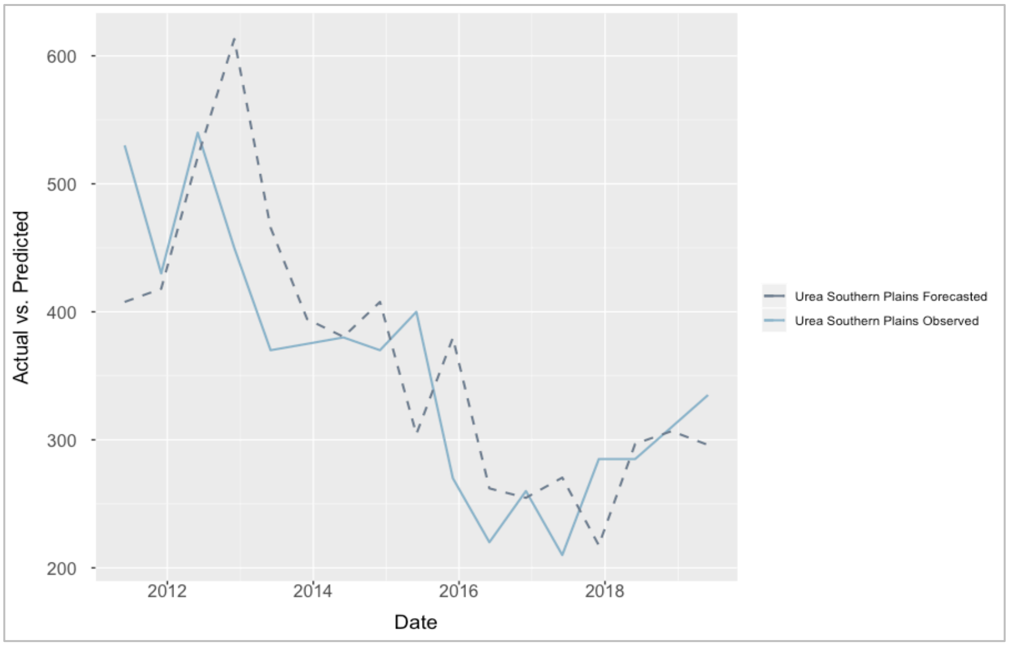

Figure B-1. Urea Southern Plains Observed and Predicted

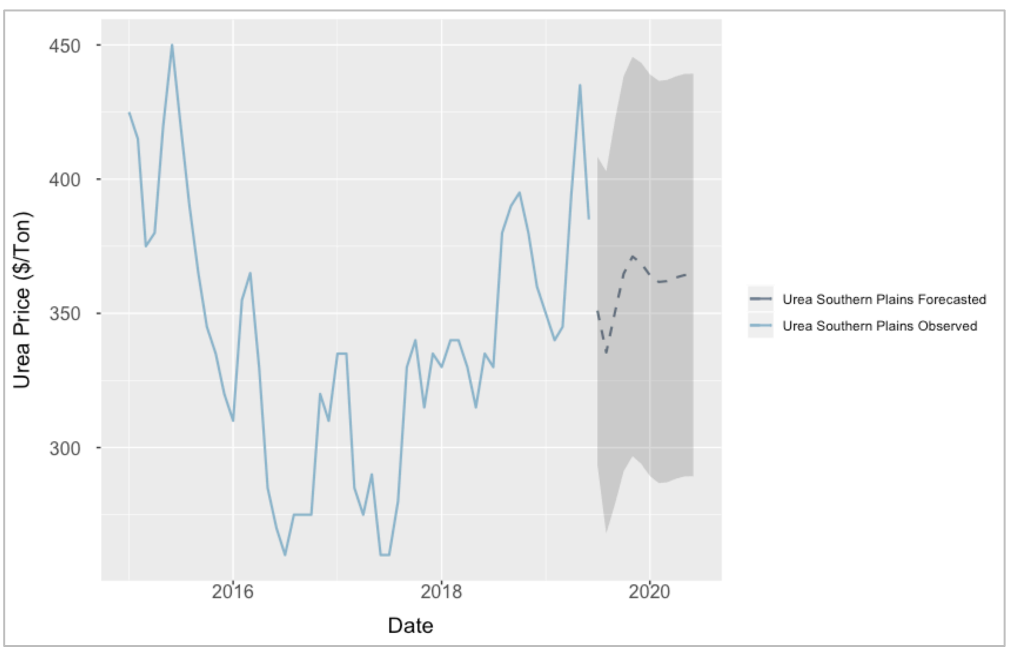

Figure B-2. Retail Forecast for Urea Southern Plains

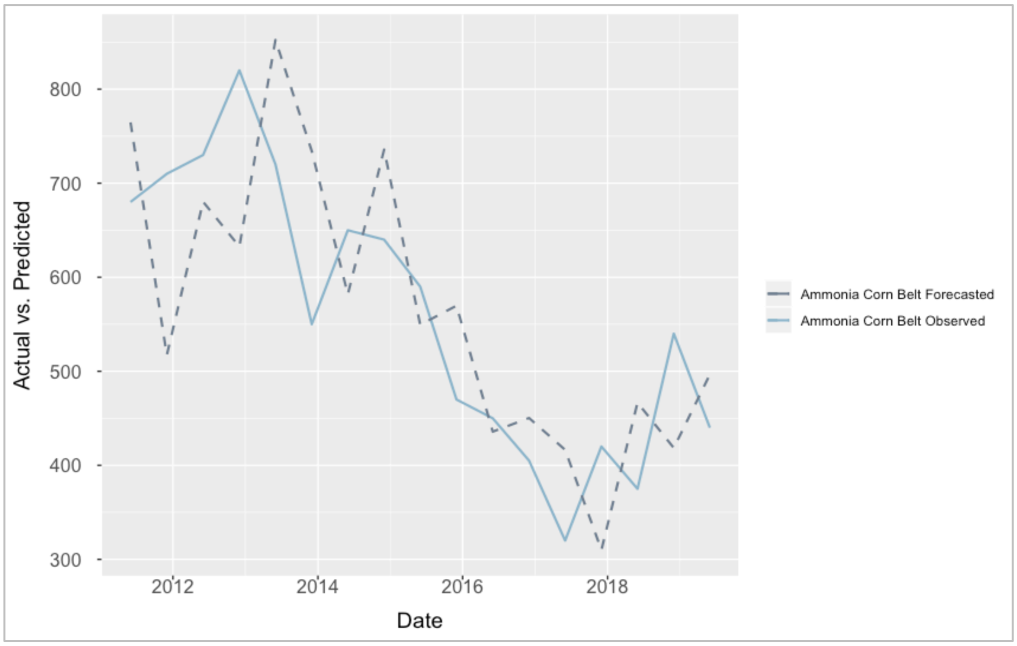

Figure B-3. Ammonia Corn Belt Observed and Predicted

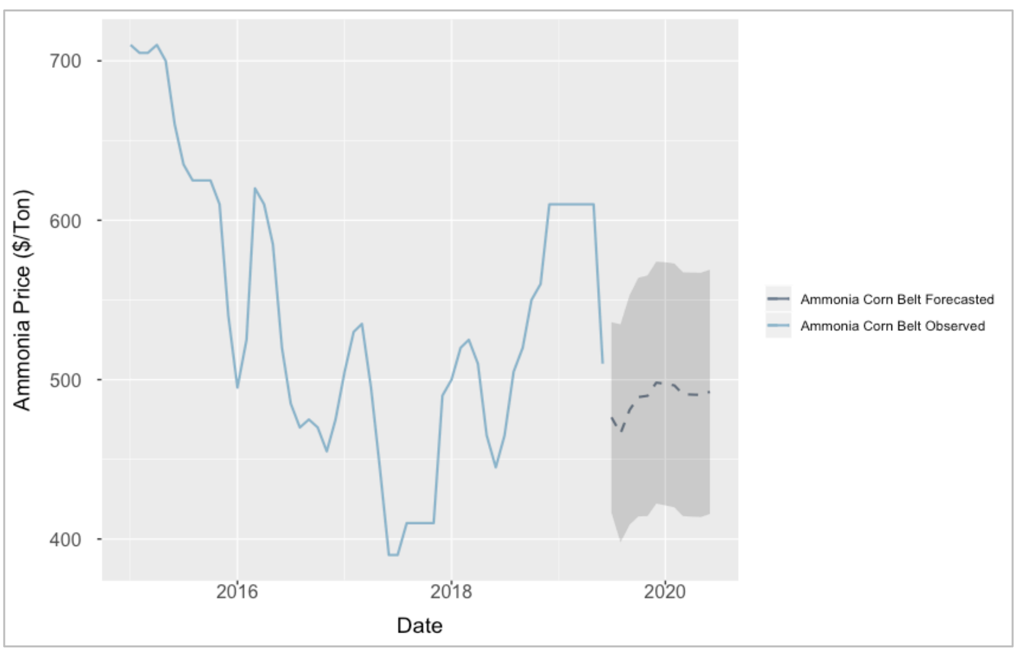

Figure B-4. Retail Forecast for Ammonia Corn Belt

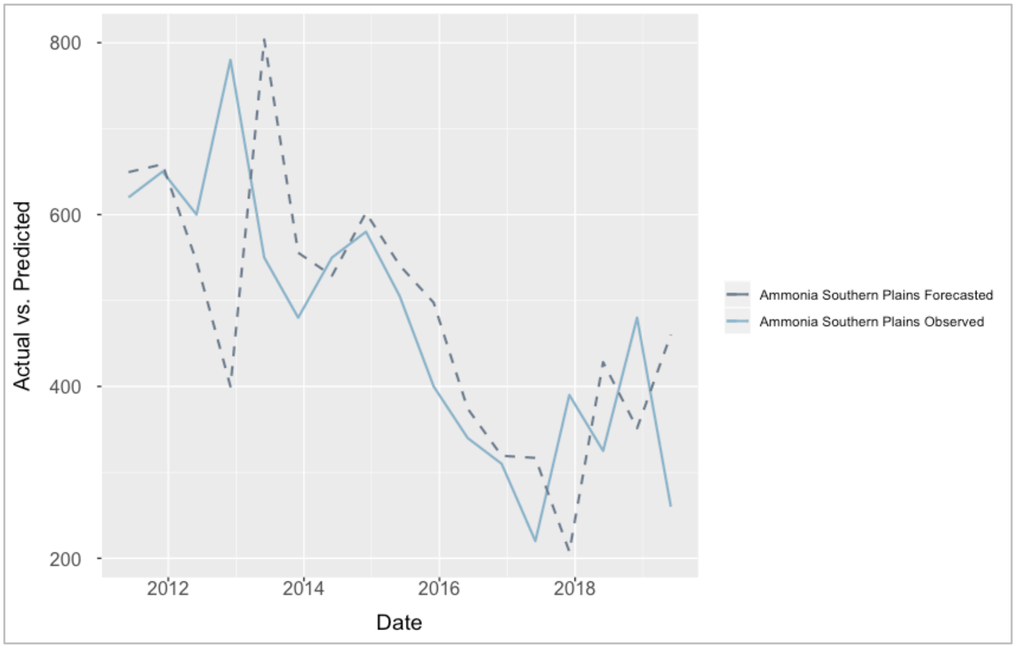

Figure B-5. Ammonia Southern Plains Observed and Predicted

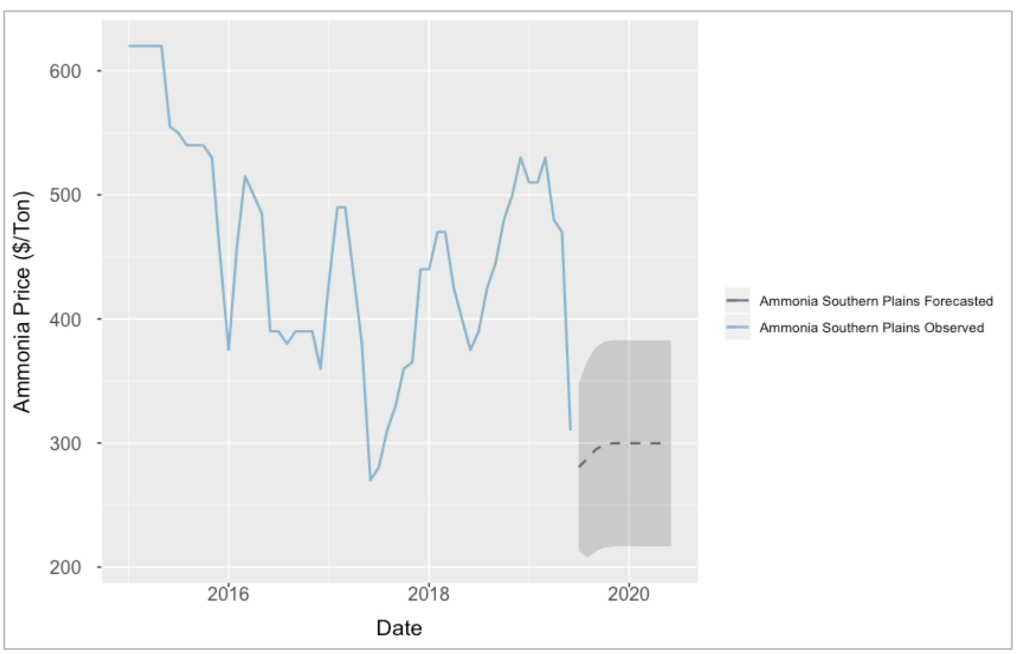

Figure B-6. Retail Forecast for Ammonia Southern Plains

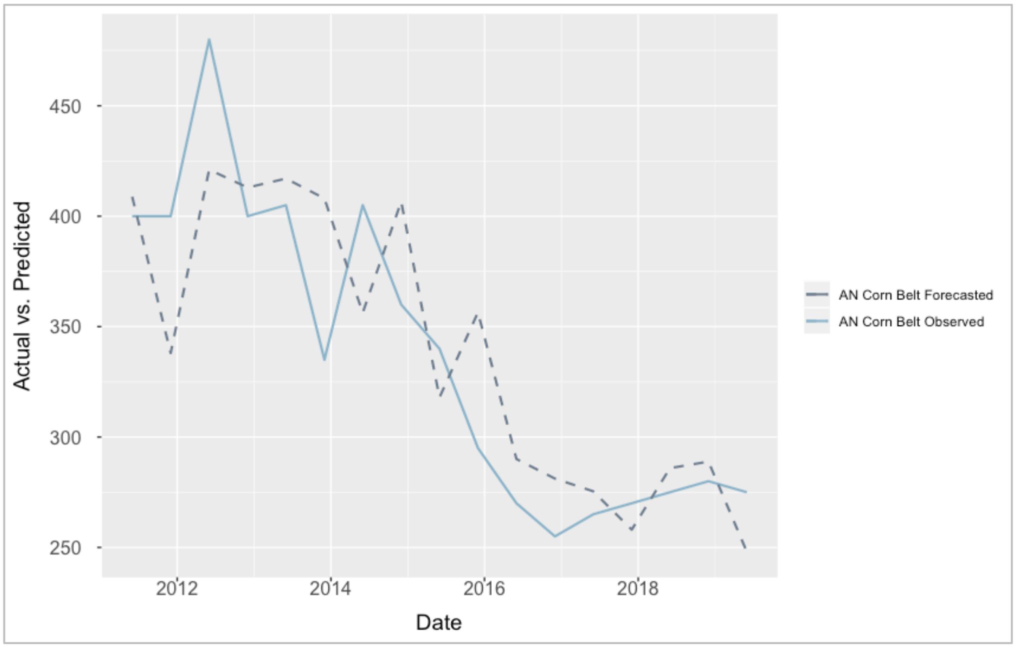

Figure B-7. Ammonium Nitrate Corn Belt Observed and Predicted

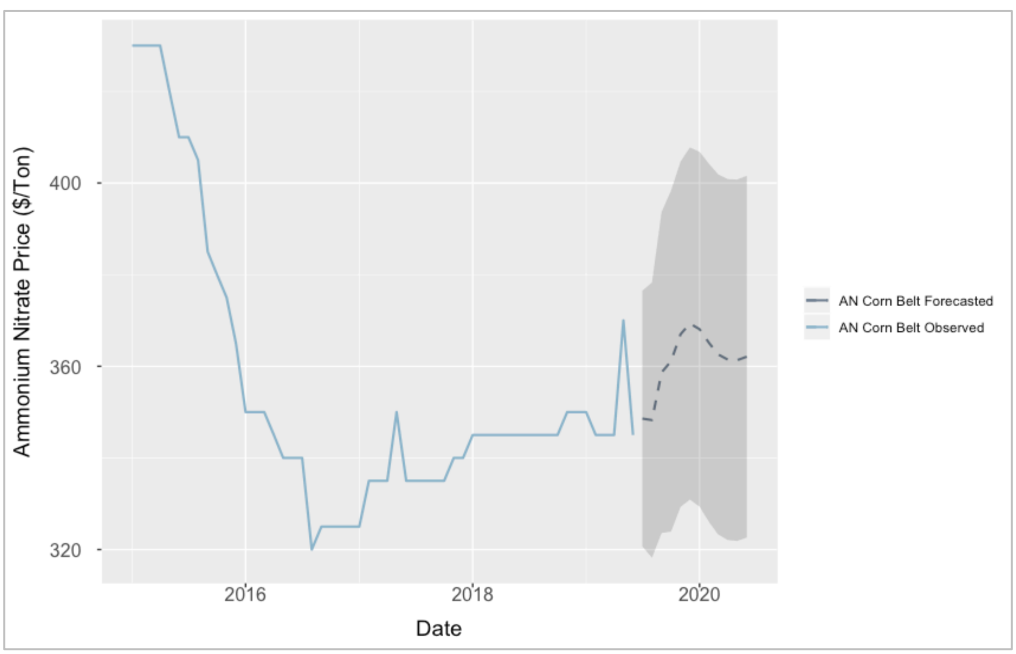

Figure B-8. Retail Forecast for Ammonium Nitrate Corn Belt

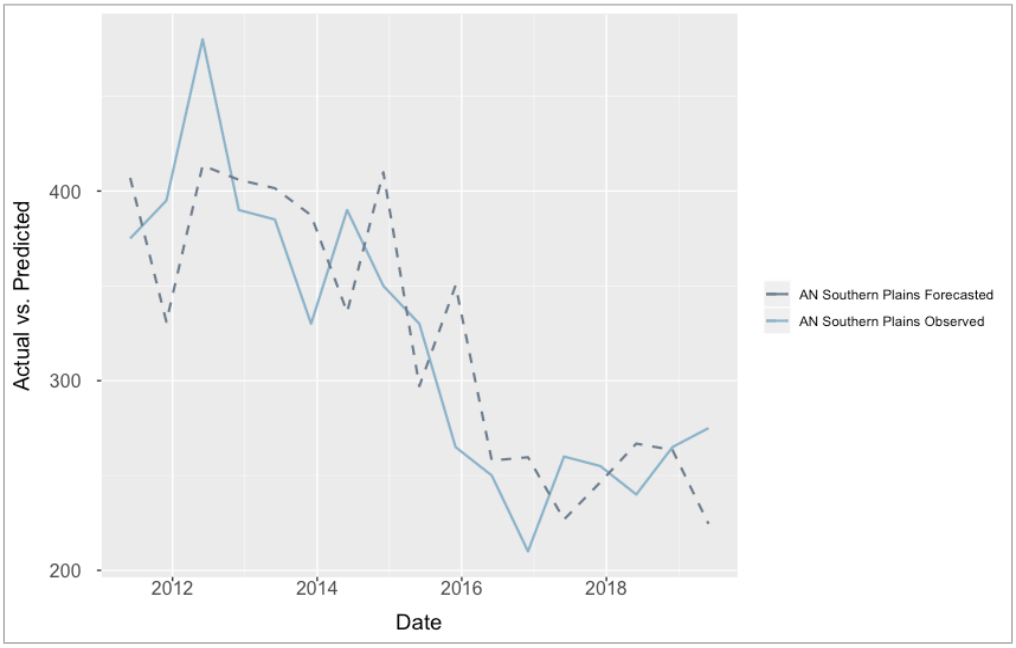

Figure B-9. Ammonium Nitrate Southern Plains Observed and Predicted

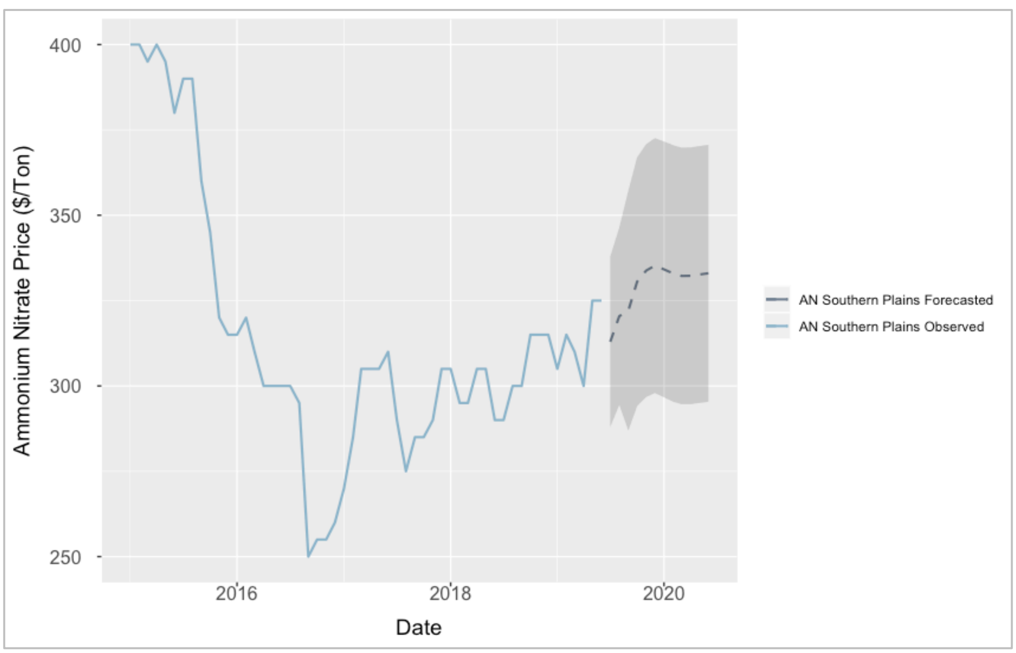

Figure B-10. Retail Forecast for Ammonium Nitrate Southern Plains

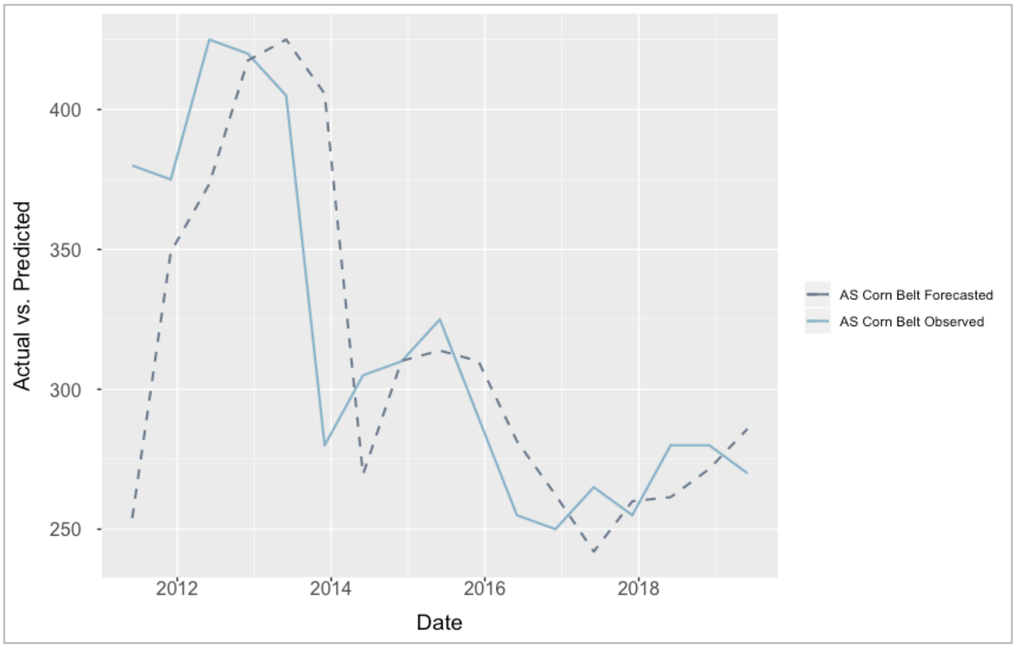

Figure B-11. Ammonium Sulfate Corn Belt Observed and Predicted

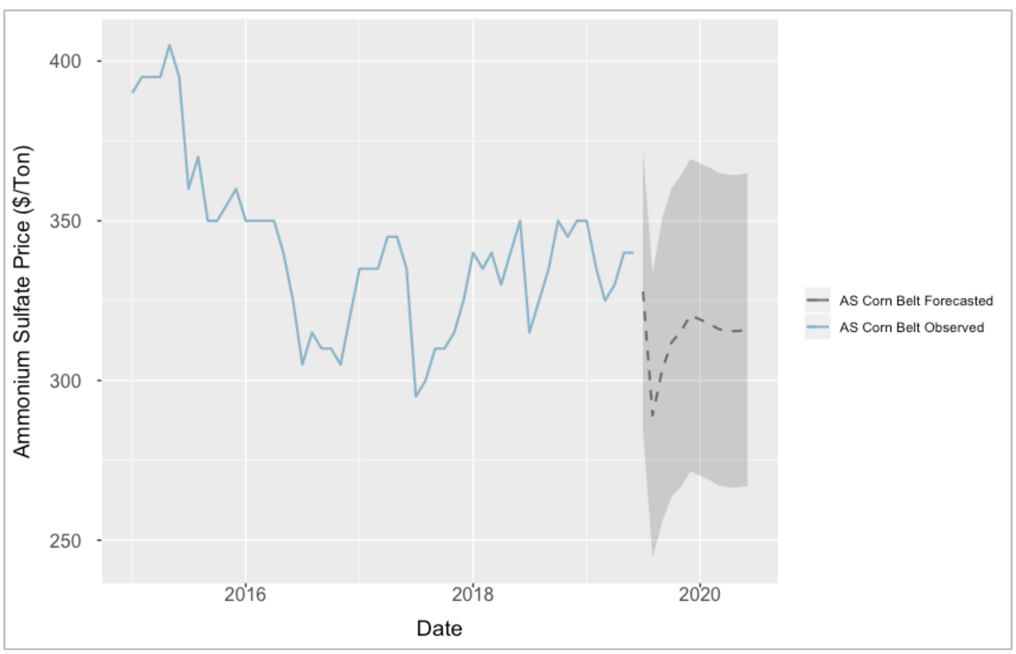

Figure B-12. Retail Forecast for Ammonium Sulfate Corn Belt

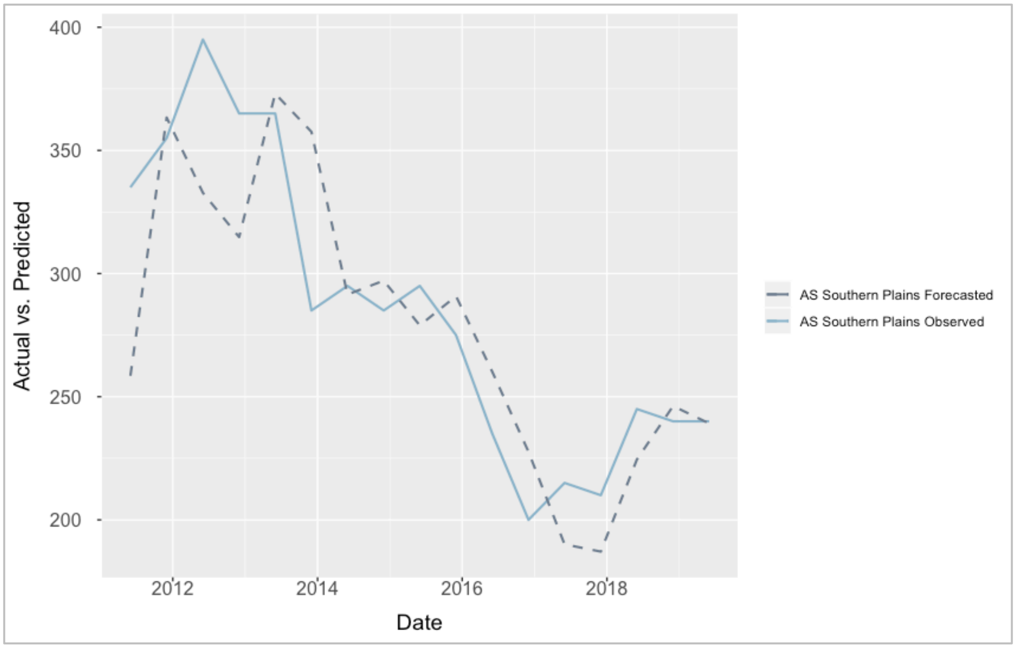

Figure B-13. Ammonium Sulfate Southern Plains Observed and Predicted

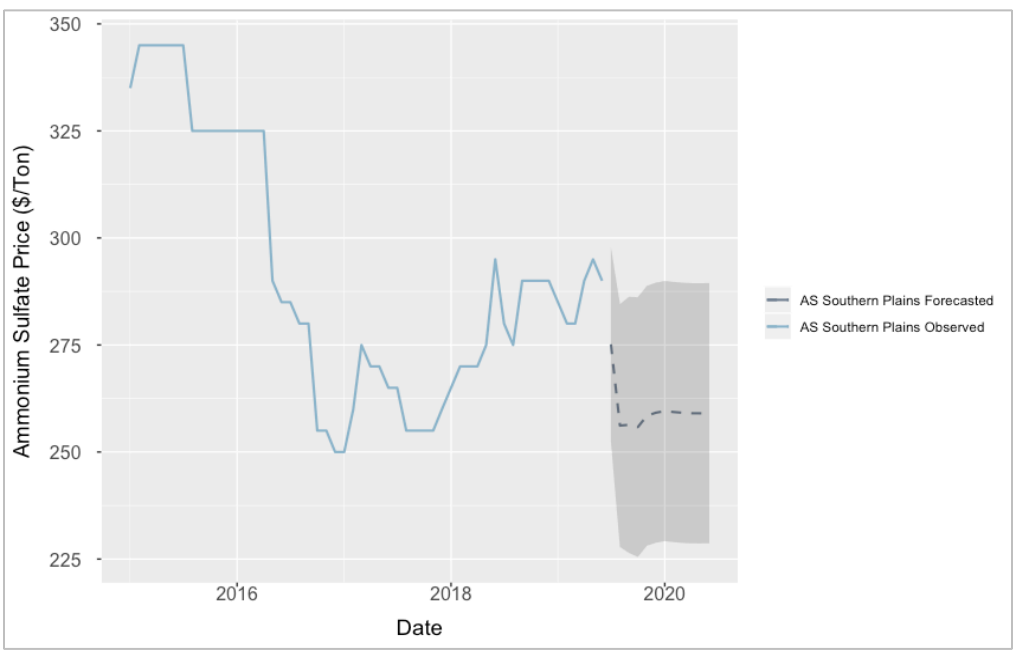

Figure B-14. Retail Forecast for Ammonium Sulfate Southern Plains

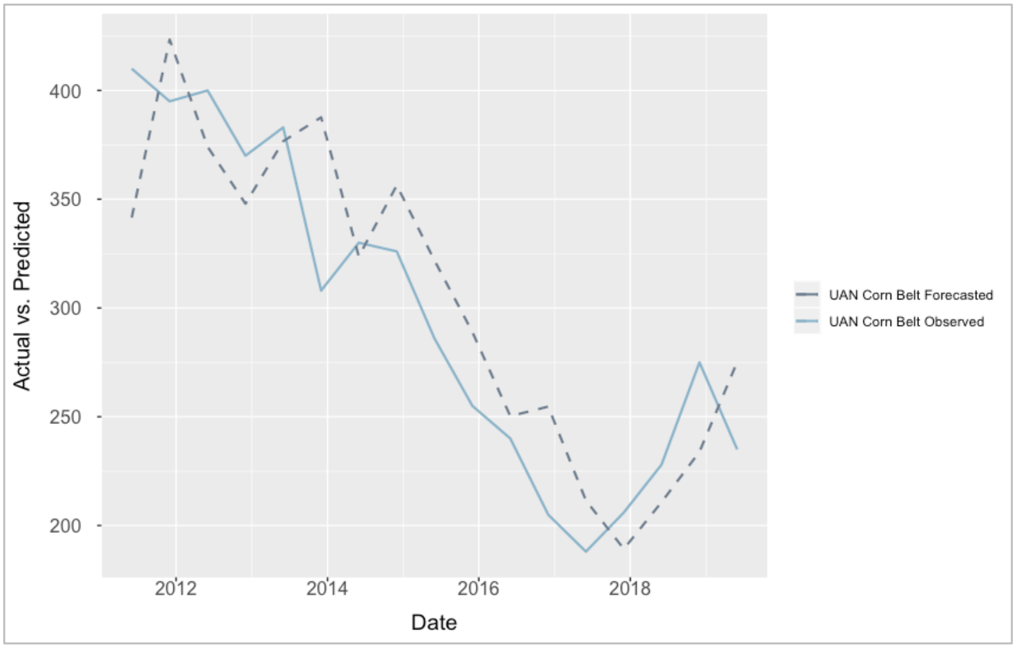

Figure B-15. Urea Ammonium Nitrate Corn Belt Observed and Predicted

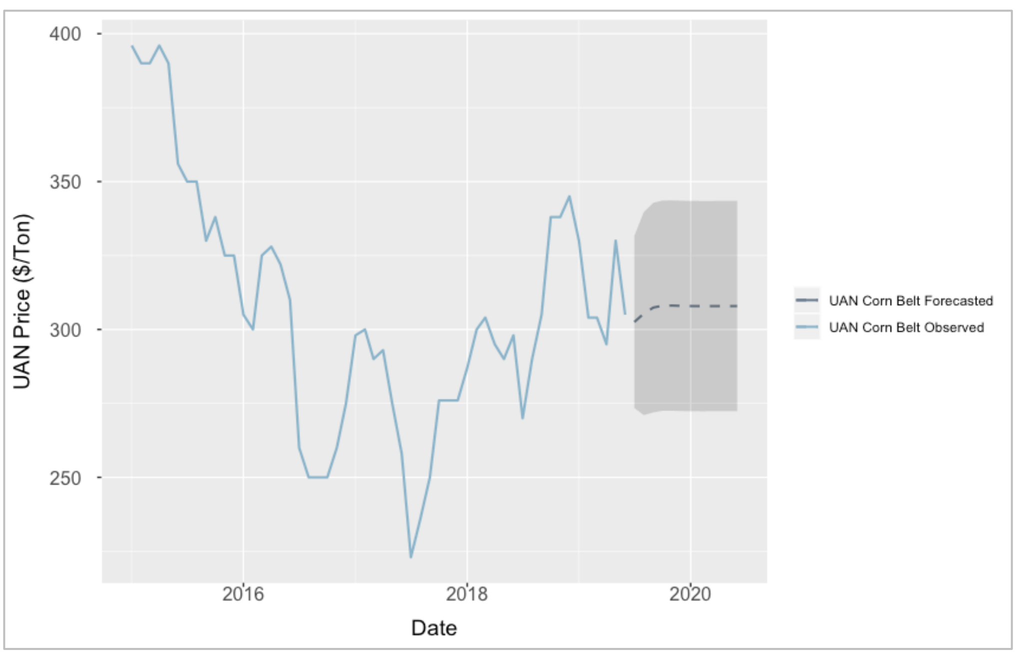

Figure B-16. Retail Forecast for Urea Ammonium Nitrate Corn Belt

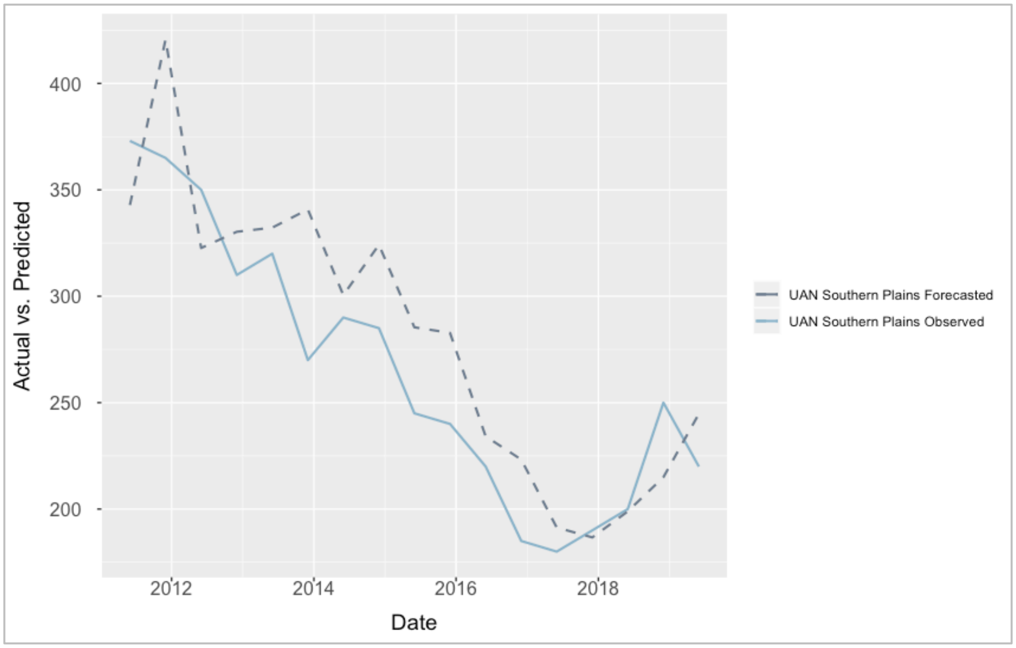

Figure B-17. UAN Southern Plains Observed and Predicted

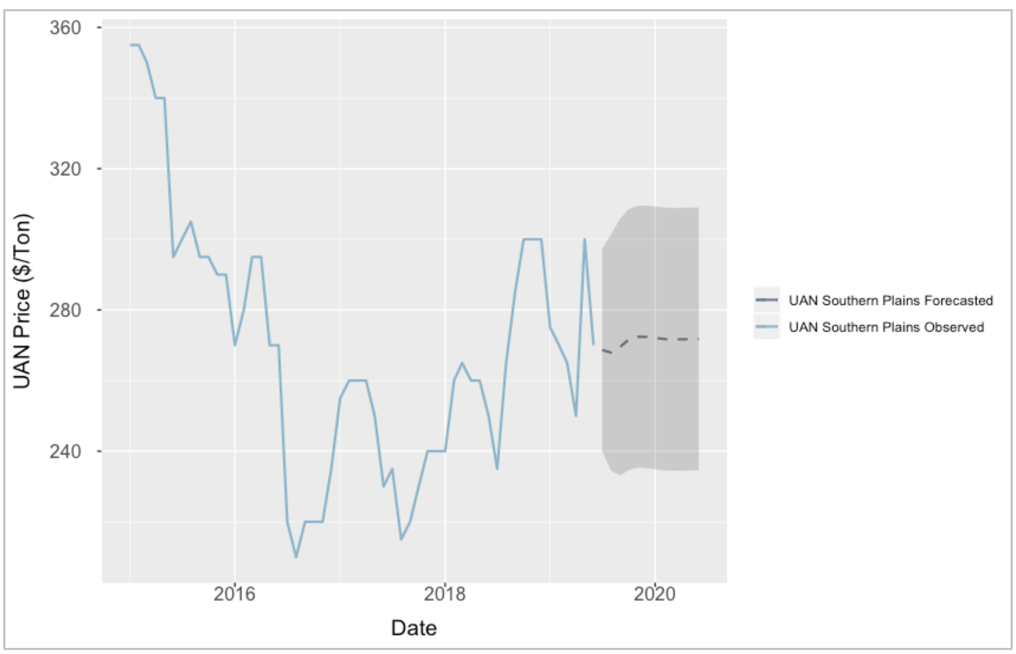

Figure B-18. Retail Forecast for UAN Southern Plains

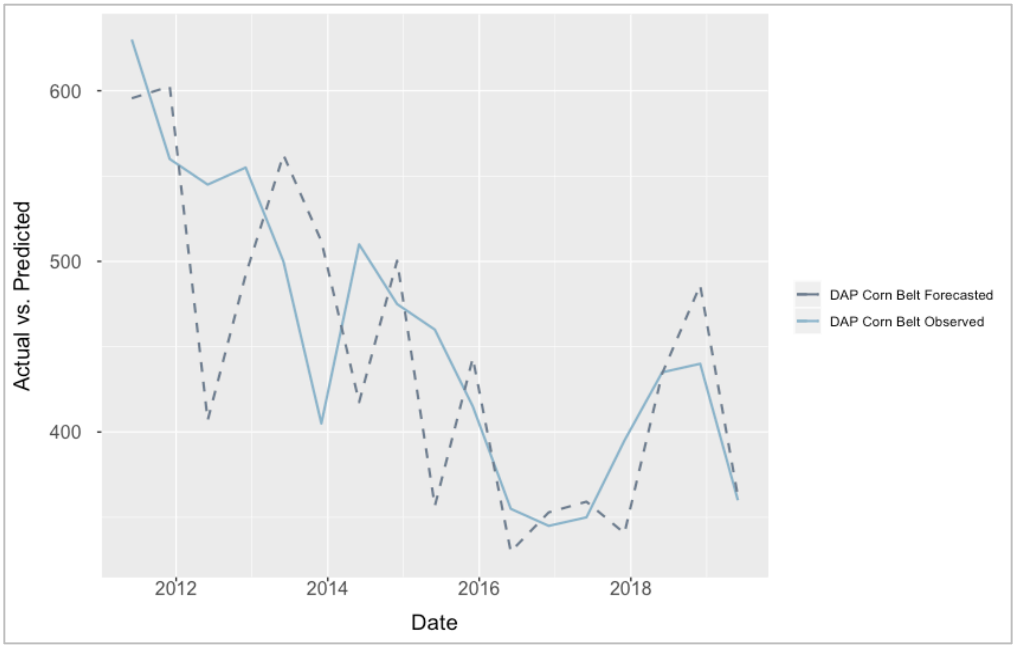

Figure B-19. Diammonium Phosphate Corn Belt Observed and Predicted

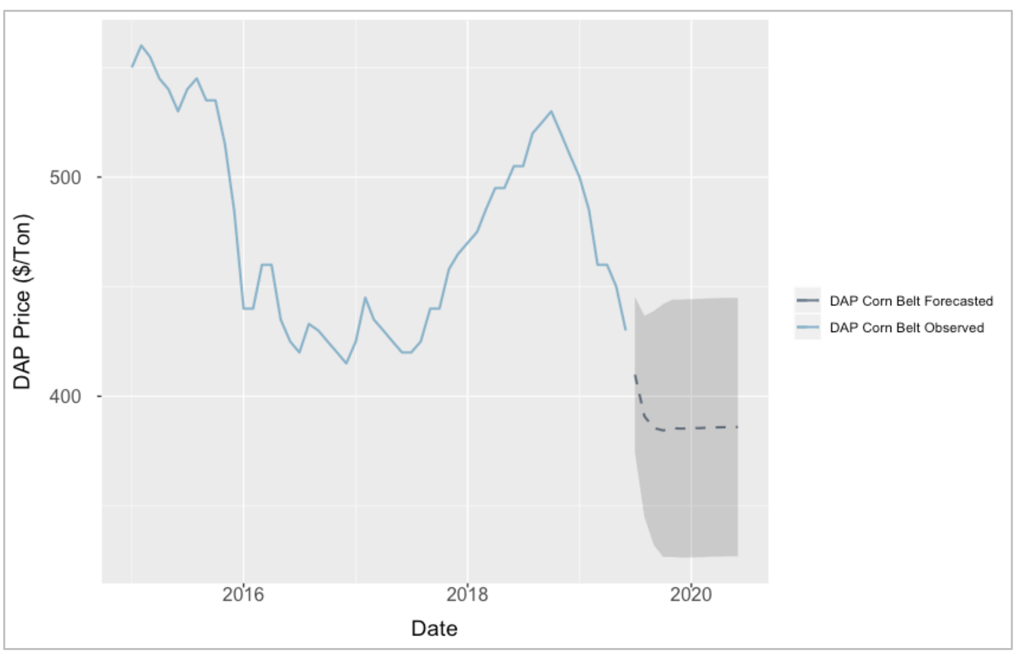

Figure B-20. Retail Forecast for Diammonium Phosphate Corn Belt

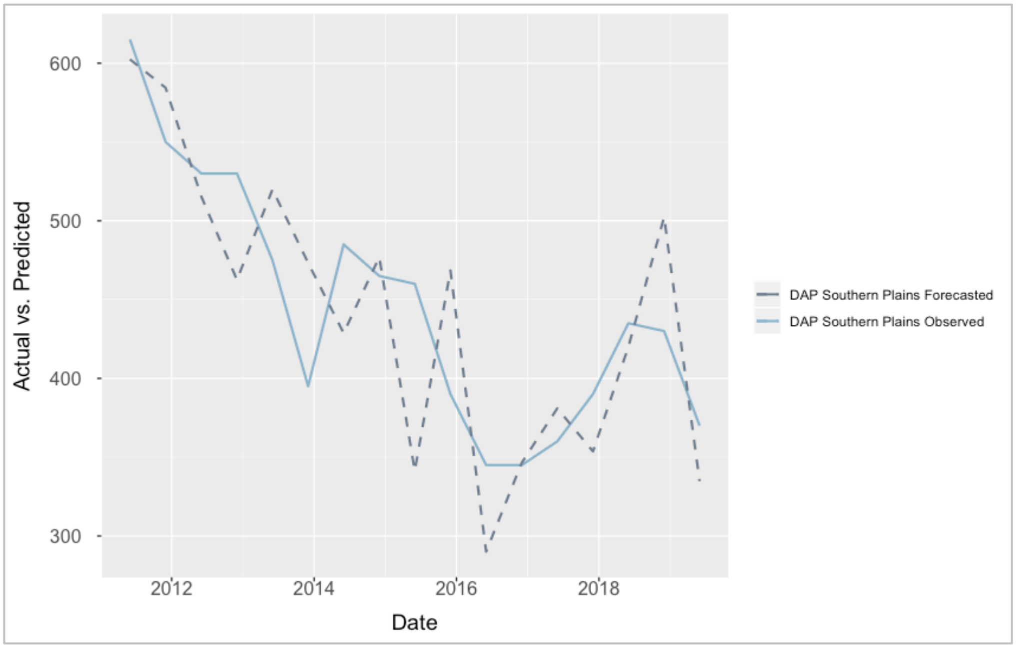

Figure B-21. Diammonium Phosphate Southern Plains Observed and Predicted

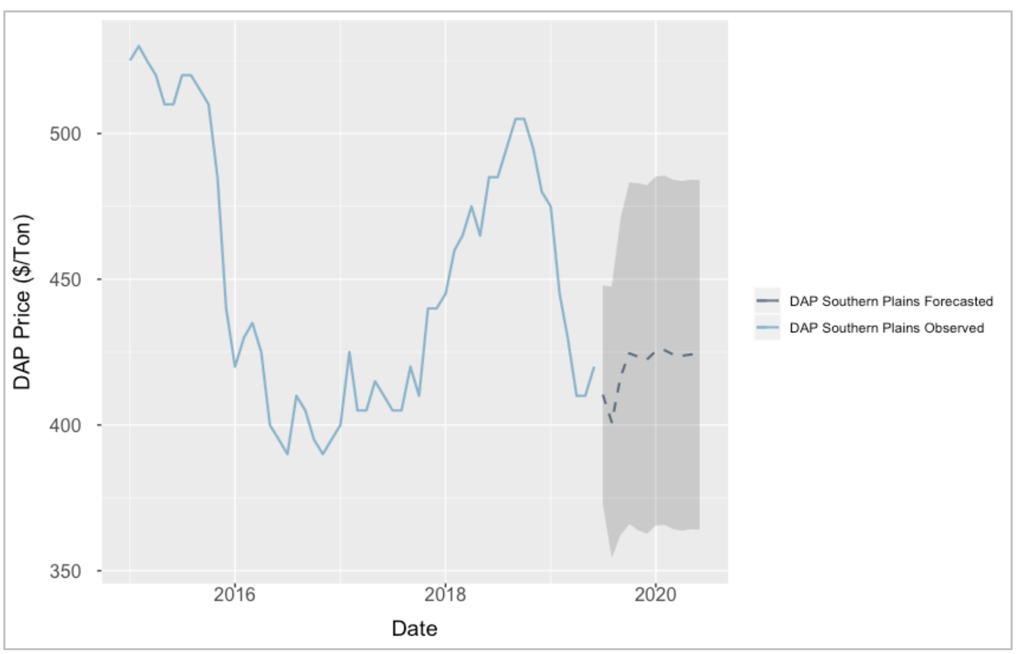

Figure B-22. Retail Forecast for Diammonium Phosphate Southern Plains

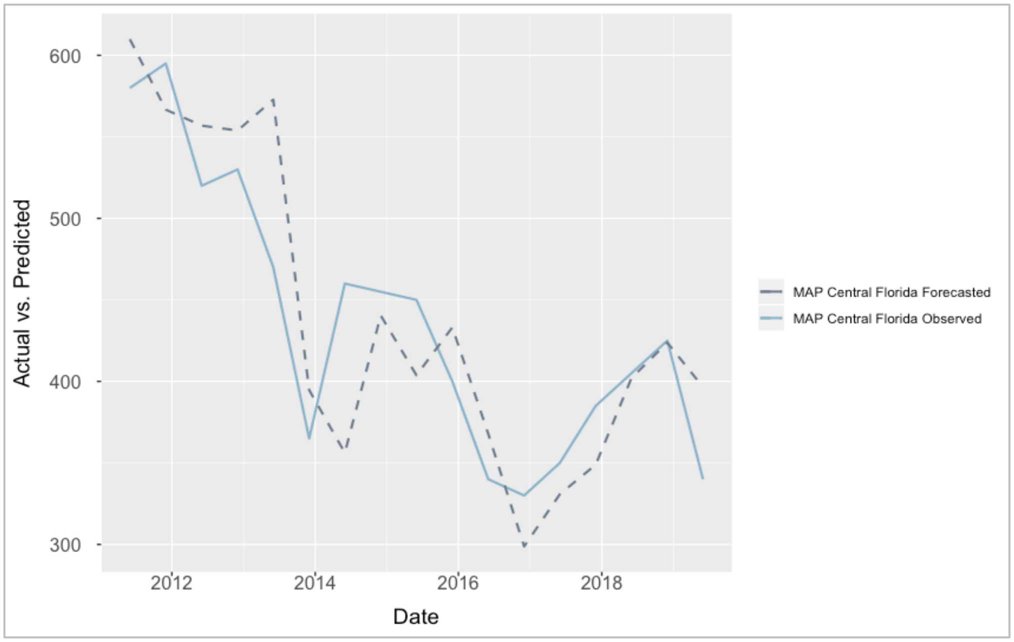

Figure B-23. Monoammonium Phosphate Central Florida Observed and Predicted

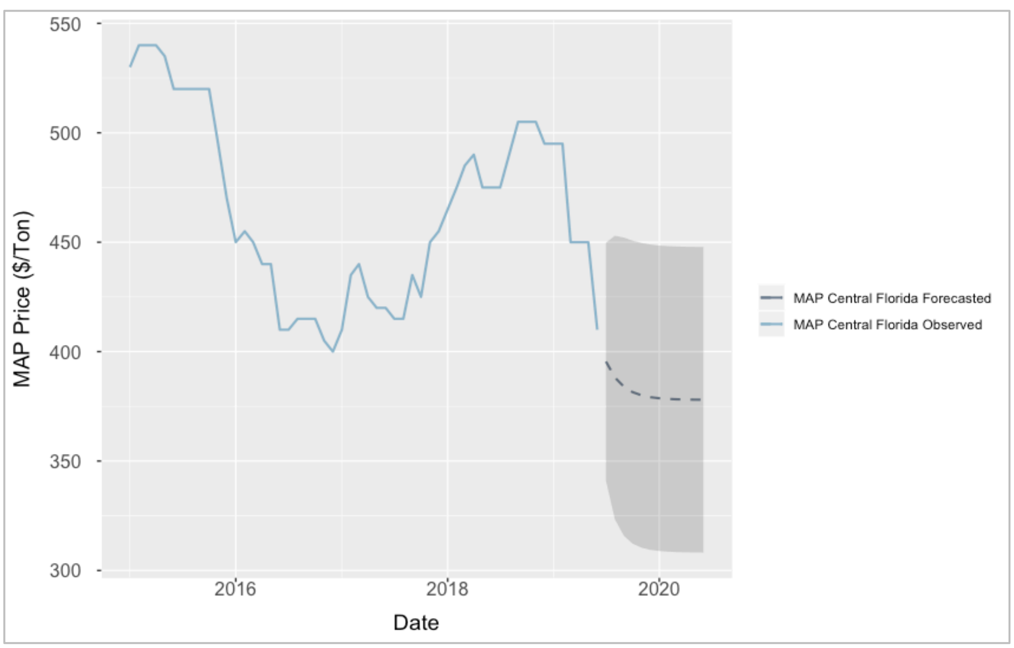

Figure B-24. Retail Forecast for Monoammonium Phosphate Central Florida

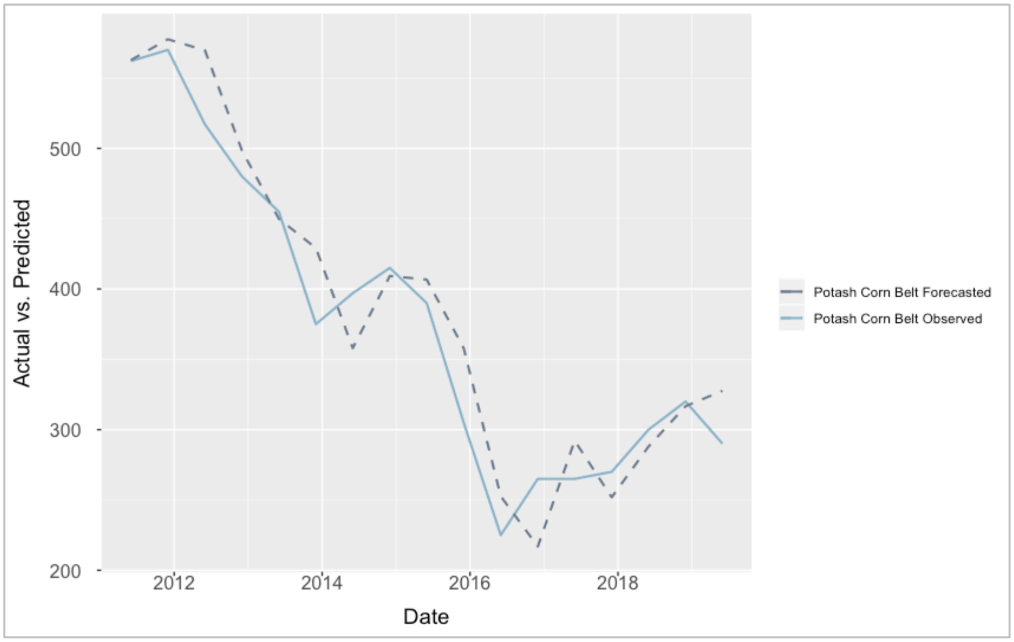

Figure B-25. Potash Corn Belt Observed and Predicted

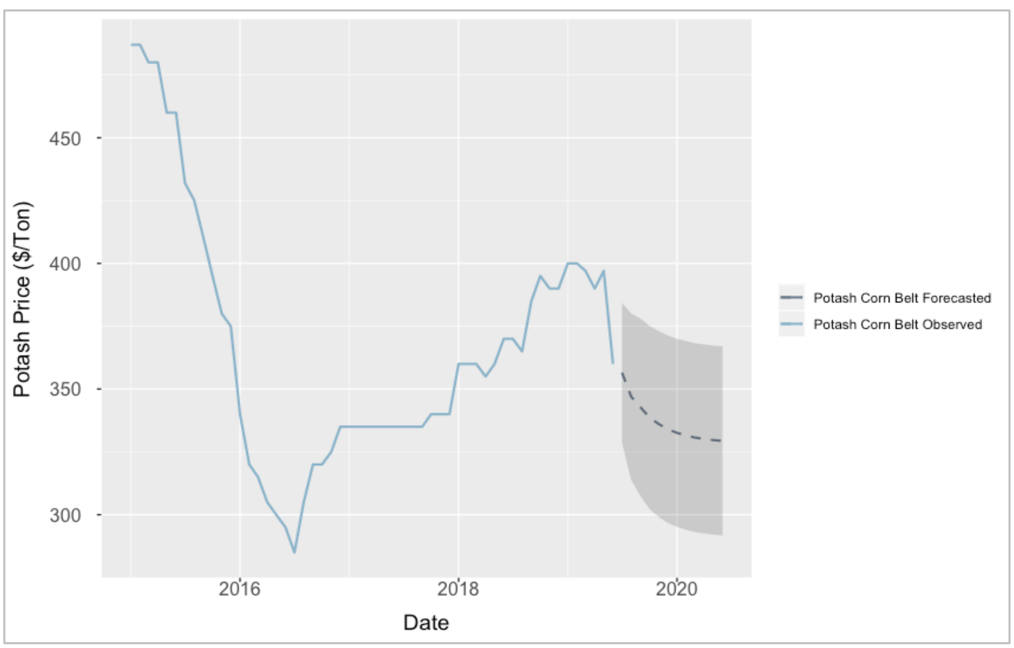

Figure B-26. Retail Forecast for Potash Corn Belt